Aalto University
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Evaluation of cloud based approaches to data quality management

Master's Thesis

Espoo, January 25, 2016

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Aalto University School of Science Degree Programme in Computer Science and Engineering Master's Programme in Service Design and Engineering	ABSTRACT OF THE MASTER'S THESIS

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Abstract: Quality of data is critical for making data driven business decisions. Enhancing the quality of data enables companies to make better decisions and prevent business losses. Systems similar to Extract Transform and Load (ETL) are often used to clean and improve the quality of data. Currently, businesses tend to collect a massive amount of customer data, store it in the cloud, and analyze the data to gain statistical inferences about their products, services, and customers. Cheaper storage, constantly improving approaches to data privacy and security provided by cloud vendors, such as Microsoft Azure, Amazon Web Service, seem to be the key driving forces behind this process.

This thesis implements Azure Data Factory based ETL system that serves the purpose of data quality management in the Microsoft Azure Cloud platform. In addition to Azure Data Factory, there are four other key components in the system: (1) Azure Storage for storing raw, and semi cleaned data; (2) HDInsight for processing raw and semi cleaned data using Hadoop clusters and Hive queries; (3) Azure ML Studio for processing raw and semi cleaned data using R scripts and other machine learning algorithms; (4) Azure SQL database for storing the cleaned data. This thesis shows that using Azure Data factory as the core component offers many benefits because it helps in scheduling jobs, and monitoring the whole data transformation processes. Thus, it makes data intake process more timely, guarantees data reliability, simplifies data auditing. The developed system was tested and validated using sample raw data.

Keywords: Data quality management, ETL, Data cleaning, Hive, Hadoop, Azure Microsoft

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Aftab Ansari

Abbreviations and Acronyms

ADF	Azure Data Factory
API	Application Program Interface
AWS	Amazon Web Service
Amazon EC2	Amazon Elastic Compute Cloud
Amazon EMR	Amazon Elastic MapReduce
Amazon RDS	Amazon Relational Database Service
Amazon S3	Amazon Simple Storage Service
CI	Confidence Interval
ETL	Extract Transform and Load
EWD	Enterprise Data Warehouse
FTP	File Transfer Protocol
HDFS	Hadoop Distributed File System
IDE	Integrated Development Environment
JSON	JavaScript Object Notation
MSDN	Microsoft Developer Network
MS SQL	Microsoft Structured Query Language
RDBMS	Relational Database Management System
SDK	Software Development Kits
SaaS	Software as Service
SQL	Structured Query Language
WASB	Windows Azure Storage Blob

Contents

Chapter 1

Introduction

In recent years, collecting and analyzing feedback from end users has become one of most important tasks for many companies who aim to improve the quality of their products or services. Regardless of being startups or corporate giants, end user feedback is crucial; hence, managing such feedback data is as significant as managing products. To increase productivity, organizations must manage information as they manage products (Wang 1998). However, it is not always easy to manage information in a large scale. The amount of end user feedback on daily basis has dramatically increased due to substantial growth in digital data. This has taken the form of big-data scenario. Big Data refers to a great volume of data that is unsuitable for typical relational databases treatment (Garlassu 2013; Fisher et al. 2012; Lohr 2012; Madden 2012). The colossal volume of data generated by the users contain valuable information that a company can utilize to understand how their products or services are performing with end users' perspective. However, processing such a massive amount of data to gain valuable insight is a major challenge. As the volume of the big data increases, it also increases the complexity and relationships between the underlying data and hence requires high-performance computing platforms to process and gain valuable insights (Wu 2014; Labrinidis & Jagadish 2012).

High quality data is data that is useful, usable, and hence fit for use by data consumers (Strong et al 1997). Currently, most information systems operate as networks, which significantly increases the set of potential data sources. On one hand, the increased number of data sources provides an opportunity to select and compare data from a broader range of data sources to detect and correct errors for improving the overall quality of data. However, this increased number of data sources also adds complexity in maintaining the overall data quality (Batini et al 2009; Haug 2013; Zhang et al 2003.) When a company makes decisions based on the available data, the quality of data is a highly important factor. Poor quality data, also known

as dirty data, can cause deleterious impact on the overall health of company (Eckerson 2002). Data is rarely 100% accurate but it can be improved by data cleaning.

Extract, Transform, and Load (henceforth ETL) is a typical process of handling data cleaning in the enterprise world where data is extracted in multiple formats and from multiple sources. ETL can be seen as a collection of tools that play a significant role in collection and discovery of data quality issues, and efficiently loading large volumes of data into a data warehouse (Chaudhuri et al 2011; Agarwal et al 2008.) One of the key purposes of a data warehouse is to enable systematic or ad-hoc data mining (Stonebraker 2002). ETL and data cleaning tools constitute a major expenditure in a data warehouse project. A data warehouse project mainly consists of two categories of expenditure: 1) one-time costs, such as hardware, software, disk, CPU, DBMS, network, and terminal analysis, and 2) recurring costs, including hardware maintenance, software maintenance, ongoing refreshment, integration transformation maintenance, and data model maintenance. (Bill 1997). However, ETL and data cleaning tools which constitute costs from both categories are estimated to account for at least one third of budget, and this number can rise up to 80%. The ETL process alone usually amounts to about 55% of the total costs of data warehouse runtime (Vassiliadis et al 2002). As such ETL is highly expensive and still includes several challenges.

To point out some key challenges and work around the ETL, Chaudhary et al. (2011) states that several data structures, optimizations, and query processing techniques have been developed over the past two decades to execute complex SQL queries, such as ad hoc queries over large volume of data. However, with accelerating growth of data, the challenges of processing data is only growing. As implied by Vassiliadis et al. (2002), it is clear that the right architecture and efficiency in data cleaning can bring notable value for both data warehouses and enterprises spending heavy budgets on data cleaning. Although ETL appears to be the dominating method of data cleaning for data quality management, there has been a number of challenges when applying ETL process to a large volume of data, which has led data scientists to find workarounds and build custom architecture for ETL process. However, with the rapid growth of data forms, volume, and velocity, the traditional ETL process that requires a proprietary data warehouse has become less relevant and not sufficiently powerful

for managing quality of Big Data. Currently, cloud-based ETL is an emerging trend mainly due to its high scalability, low cost, and convenience in development and deployment. This thesis aims to leverage tools and services offered by cloud providers and build a cloud based ETL system for managing the quality of data.

1.1 Research goals

This thesis has three aims: background study, propose architecture, and implementation. The main objective of this thesis is to build a cloud based ETL system for data quality management. To achieve this objective, this thesis evaluates an existing cloud based approach similar to ETL for managing data quality and then proposes a new, efficient and scalable architecture. The new architecture can also harness the strength of machine learning in data quality management.

To understand better the practical implications of this cloud based approach, a sample telemetry data provided by the client company is processed aiming to improve its quality. The efficiency and scalability of data quality management is evaluated based on the obtained results. The proposed architecture is compared against other similar data quality management systems' architecture to ensure the validity. When processing the sample data (which contains dirty data), false positives are identified and minimized to ensure better conclusions. Dirty data can lead to the wrong conclusions being made, which is often classified as a false positive. For example, if data suggests that the average battery life of a mobile device is x hours when it is not, that is a false positive. In data cleaning, statistical rules can be applied to detect and remove incorrect data in order to minimize false positives. This uses statistical methods to investigate how false positives can be minimized and how the confidence interval can be quantified for the sample data. This thesis proposes that a key component of the data quality management system is data pipelines. Data pipeline features of the Amazon and Azure platforms are also compared in order to determine the key differences.

1.2 Research questions

This thesis aims to determine strategies for ensuring data quality management using the latest and most efficient cloud based technologies and approaches. The thesis focuses on the following four research questions.

- RQ1: What is the most suitable architecture for data quality management in the cloud?

Chapter 3 presents alternative cloud based tools for data quality management. With the evaluated tools, an architecture is designed and proposed which aims to satisfy requirement of improved data quality management. The proposed architecture is compared against the architecture of a research project named "CARAT" and "CloudETL".

- RQ2: How to minimize false positives when applying automatic data cleaning?

Chapter 5 discusses the process of minimizing false positives in automatic data cleaning in detail. First data cleaning is performed on a sample telemetry dataset by using the proposed architecture of this thesis. Section 3.2 discusses about the proposed architecture in detail. Data cleaning rules are defined using Hive scripts to detect and remove incorrect data and minimize the false positives. To perform automatic data cleaning, this thesis uses cloud based Hadoop clusters offered by Microsoft Azure's HDInsight, which supports Hive query and can be run on demand. A monitoring mechanism for applied data cleaning rules is developed to visualize the performance and progress of the applied cleaning rules. Microsoft's Azure Data Factory (ADF) provides monitoring mechanism for data cleaning rules.

- RQ3: How to quantify confidence interval for the false positive rate?

Chapter 5 presents the details of the process of quantifying confidence interval for the false positive rate of the data cleaning rules. A confidence interval of 95% is calculated for each false positive rate of cleaning rules using the binomial distribution. An R-script is used to calculate 95% confidence interval.

- RQ4: What are the advantages of using cloud technologies instead of creating custom data cleaning rules?

Chapter 2 discusses various advantages of using cloud technologies in the context of data cleaning. This thesis also investigates the key advantages of cloud technologies based on various literature.

1.3 Structure of this thesis

This thesis is organized as follows. Chapter 2 presents a background study about data quality management. It highlights the importance of data cleaning in the current context of increasing volume, velocity, and diversity of data. Two related projects and their architectures are studied briefly in this chapter. Chapter 3 describes in detail the description of the implemented Azure Data Factory. The architecture in general and its key components are described. Some example code snippets are presented to demonstrate how other tools and technologies on Azure platform can be integrated with Azure Data Factory. Chapter 4 describes briefly the sample data processed using the Azure Data Factory. This chapter also discusses the identified data quality problems in the sample data, selection and assessment of data cleaning rules. Chapter 5 discusses the results of the sample data cleaning over the implemented Azure Data Factory. Chapter 6 concludes the thesis and presents suggestions for future development.

Chapter 2

Background

This thesis presents background studies with two main perspectives: (1) architectural background which studies cloud based architectures implemented for data quality management and discusses examples of related work, (2) data quality management which studies about the challenges of data quality management. Data cleaning in particular is studied as a technique to improve the quality of data. Moreover, the advantages of using cloud technologies for managing quality of data is discussed.

2.1 Architectural background

Chaudhuri et al. (2011) argues that since more data is generated as digital data, there is an increasing desire to build low-cost data platforms that can support much larger data volume than that traditionally handled by relational database management systems (RDBMSs). Figure 1 shows typical architecture of handling data for business intelligence in the enterprise environment.

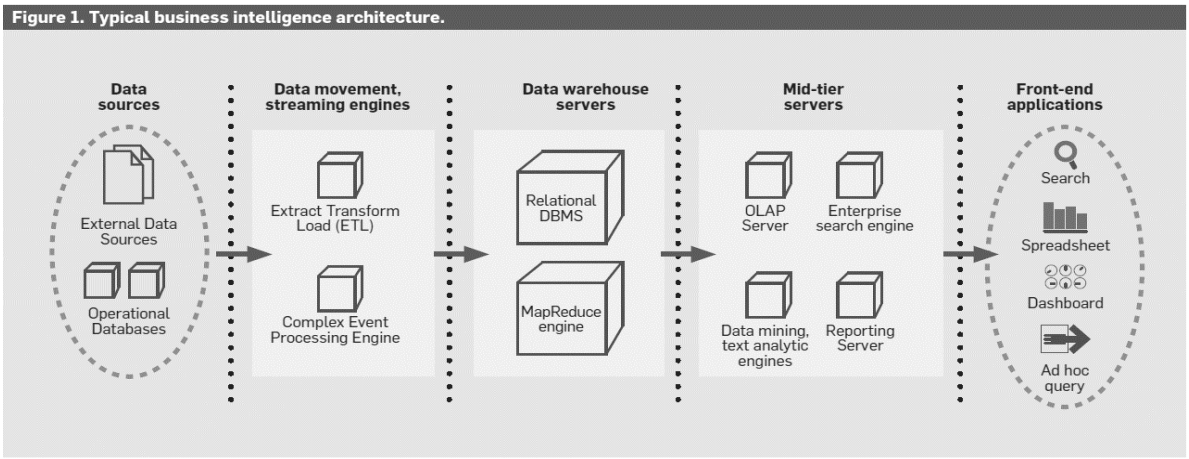


Figure 1. Typical business intelligence architecture (Chaudhuri 2011, p. 90)

As can be seen from Figure 1, data can come from multiple sources. These sources can be operational databases across departments within the organization, and external vendors. As these different sources contain data in different formats, and volume, there are inconsistencies and data quality issues to deal with when integrating, cleaning, and standardizing such data for front-end applications (Roberts et al. 1997; Vijayshankar & Hellerstein 2001). Moreover, traditional ETL process architectures do not seem to be a good fit for solving Big Data challenges as currently digital data is growing rapidly and the architecture for data integration needs to support high scalability. This is mainly because cloud providers offer highly scalable data storage, and data processing tools and services which makes it easy to store, integrate, process, and manage data. In addition, services offered by cloud providers cost less than own data warehouse solution due to the economy of scale.

The cloud is all about unlimited storage and compute resources to process data which come from diverse sources and are of big volume, and velocity (Maturana et al. 2014). Data collection has become a ubiquitous function of large organizations for both record keeping and supporting variety of data analysis tasks to drive decision making process (Hellerstein 2008; Thusoo et al. 2010). Leveraging data available to business is essential for organizations and there is a critical need for processing data across geographic locations, on-premises, and cloud with a variety of data types and volume. The current explosion of data form, size, and velocity is a clear evidence of the need for one solution to address today's diverse data processing landscape (Microsoft Azure 2014; Boyd & Kate 2012). Despite the importance of data collection and analysis, data quality is a pervasive problem that almost every organization faces (Hellerstein 2008). Therefore, one of the key requirements of such solution should be the ability to manage the data quality as data integration from diverse data source, format only adds complexity in data quality.

Currently, the fundamental difficulties for data scientists in efficiently searching for deep insights in data are (a) identifying relevant fragments of data from diverse data sources, (b) data cleaning techniques such as approximate joins across two data sources, (c) progressively

sampling results of query, (d) obtaining rich data visualization which often requires system skills, and algorithmic expertise (Chaudhuri 2012.)

According to Redman (as cited in Redman 1998), issues of data quality can be categorized in main four categories: (1) Issues associated with data "view". These are typically the models of real world data that include relevancy, granularity, and level of detail; (2) Issues associated with data values such as accuracy, consistency, and completeness; (3) Issues associated with presentation of data which can be format, and ease of interpretation; (4) Other Issues which can be associated with privacy, security, and ownership.

2.1.1 Related work to data quality management

Three contributing communities (1) Business analysts, (2) solution architects, and (3) database experts and statisticians (Sidiq et al 2011) are behind the development of newer systems for data quality management. MapReduce paradigm (chaudhary 2011; Roshan et al 2013) for data management architecture including Hadoop Distributed File System (HDFS) (Kelley 2014; Stonebraker et al 2010) is a well-known approach among current solutionists for Big Data solution providers. To ease the life of programmers who prefer structured query language (SQL) over MapReduce framework, several SQL like language have been developed over the years that can work on top of MapReduce. These include Sawzall, Pig Latin, Hive, and Tenzing (Sakr & Liu 2013). The ETL system implemented as part of this thesis is built to support Big Data scenario which uses Hadoop and Hive for its data cleaning process.

Apache Hadoop

Apache Hadoop is a framework for distributed processing of large data sets across clusters of computers using simple programming models (Apache Org, 2015). It is an open source implementation of the MapReduce framework. Engines based on MapReduce paradigm (which was originally built for analyzing web documents and web search query logs) are now

being targeted for enterprise analytics (Chaudhuri 2011; Herodotos et al 2011). To serve this purpose, such engines are being extended to support complex SQL-like queries essential for traditional enterprise data warehousing scenarios. Dahiphale (2014) explains MapReduce as a framework developed by Google that can process large datasets in distributed fashion. Further, pointing out the two main phases of MapReduce framework namely Map phase and Reduce phase, it provides an abstraction of these two phases. During the Map phase, input data is split into chunks and distributed among multiple nodes to be processed upon by a user defined Map function. In Reduce phase, data produced by Map function is aggregated. Below is an example of doing word count using MapReduce.

Texts to read:

```
1  Hello World Bye World
2  Hello Hadoop Goodbye Hadoop
```

The Map function reads words one at a time and outputs:

```
1  (Hello, 1)
2  (World, 1)
3  (Bye, 1)
4  (World, 1)
5  (Hello, 1)
6  (Hadoop, 1)
7  (Goodbye, 1)
8  (Hadoop, 1)
```

The shuffle phase between Map and Reduce phase creates a list of values associated with each key which becomes input for Reduce function.

```
1  (Bye, (1))
2  (Goodbye, (1))
3  (Hadoop, (1, 1))
4  (Hello, (1, 1))
   (World, (1, 1))
```

5

Finally the Reduce function sums the numbers in the list for each key and outputs (word, count) pairs as given below.

```
1  (Bye, 1)
2  (Goodbye, 1)
3  (Hadoop, 2)
4  (Hello, 2)
5  (World, 2)
```

Jayalath et al. (2014) describes an implementation of MapReduce framework such as Apache Hadoop as part of standard toolkit for processing large data sets using cloud resources.

Data cleaning and standardizing using cloud technologies seems to be emerging as a replacement of traditional ETL processes. Some of the key cloud platforms including Amazon Web Services (AWS), and Microsoft Azure have been offering services such as data pipelines for data integration, and computing service. These services supports parallel reading using technologies including MapReduce, Hive, and Pig running in settings such as Hadoop.

Apache Hive

Apache Hive is a data warehouse software that facilitates querying and managing large datasets stored in distributed storage such as HDFS (Apache Hive Org 2015). Syntax wise, Hive can be considered as SQL-like query language which runs MapReduce underneath. Currently, the use of Hive is increasing among programmers who are more comfortable with SQL like languages and not Java. For Big Data architecture built around Hadoop system, Hive seems to be one of the popular choices apart from other languages such as Pig or Java. This thesis proposes an architecture for cloud based ETL that uses Hive as a query language to perform data cleaning.

Big Data architecture

Mohammad & Mcheick & Grant (2014) points out that the central concept to Big Data architecture context is that data is either streaming in or some ETL processes are running within organizational environment with which they have some relationship in terms of organizational or analytical needs. Mohammad et. al. (2014) further argues that producing both input and output data streams using Hadoop/MapReduce, Hive, Pig or some other similar tools, has an effect on organizational environment where stakeholders are required to directly or indirectly produce these data streams.

Cloud based ETL

Various research works highlight the ever increasing volume, velocity, and diversity of data and emphasize the need for a cloud-based architecture which is more robust than traditional ETL. These includes a research done at Microsoft; "What next? A Half-Dozen Data Management Research Goals for Big Data and the Cloud" (Chaudhuri, 2012), research work by (Kelly 2014) about "A Distributed Architecture for Intra-and Inter-Cloud Data Management", another recent research on "Big Data Architecture Evolution: 2014 and Beyond"(Mohammad et. al. 2014). The largest cloud vendors such as Amazon, Microsoft, and Google have started offerings that follow Hadoop, analytics, and streams. A few examples for such services are: Amazon's EMR, DynamoDB, RedShift, and Kinesis; Microsoft's HDInsight, Data Factory, Stream analytics, and Event Hub; Google's Hadoop, BigQuery, and DataFlow. These big cloud vendors aim to provide a Big Data Stack (Bernstein 2014) that can be used to architect cloud based ETL.

Several cloud based architectures have evolved to address the challenge of processing massive amount of structured and unstructured data collected from numerous sources. In addition, this trend is constantly growing. E.g., CARAT has developed its own architecture

built by using different tools and services available on Amazon platform for processing ever growing telemetry data. Section 2.1.2 deals with the architecture of CARAT in detail. Recently, Microsoft announced a service named Azure Data Factory claiming it a fully managed service for composing data storage, processing, and movement services into streamlined, scalable, and reliable data production pipelines. Azure Data Factory is covered in detail in Section 2.2.2. Azure Data Factory being the newest technology in the market, this thesis aims to study Azure Data factory in detail and propose an architecture for data quality management that utilizes Azure Data Factory and other tools and services available on Azure platform.

2.1.2 CARAT

CARAT is a battery awareness application that collects data from the community of devices where it is installed. The collected data is processed by the Carat Server, and stored. There is a Spark-powered analysis tool that extracts key statistical values and metrics from the data (Carat 2015). The CARAT server correlates running applications, device model, operating system, and other features with energy use. CARAT application provides actionable suggestions and recommendations based on the data for enabling users to improve battery life (Athukorala et al 2014). Figure 2 shows an architecture of CARAT.

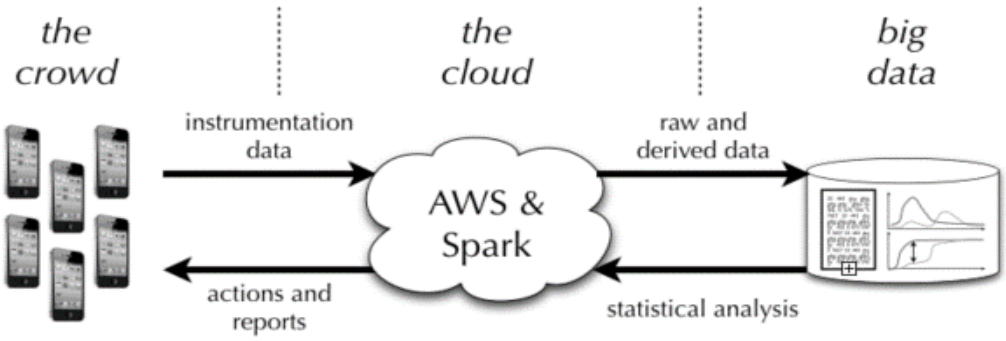


Figure 2: Architecture of CARAT's data processing (Athukorala et al 2014)

As can be seen from the architecture of CARAT, the architecture seems to support Big Data scenarios. One of the reasons CARAT is a perfect example of related work for this thesis is

that CARAT processes the data collected from mobile devices by performing statistical analysis in cloud. The telemetry sample data which is processed in this thesis work also comes from mobile devices. The CARAT architecture is built on AWS platform and uses Spark. Instead of AWS and Spark, this thesis suggests to use other tools such as ML Studio and R script on the Microsoft Azure platform. Spark is supported by Azure HDInsight also but it cannot be connected via ADF pipelines yet. However, ADF provides support for ML Studio which has a number of powerful machine learning algorithms as well as support for R script. In addition, ADF supports *Mahout* for statistical analysis that requires machine learning algorithms. ADF seems to be more promising as monitoring and management of the ETLs via ADF is much simpler than in the Carat case.

2.1.3 CloudETL

CloudETL is an open source based ETL framework that leverages Hadoop as its ETL execution platform and Hive as warehouse system. CloudETL is composed of a number of components that includes APIs, ETL transformers, and Job manager. The API is used by the user's ETL program. The job of ETL transformers are to perform data transformation. The job manager is responsible for controlling the execution of jobs submitted to Hadoop.

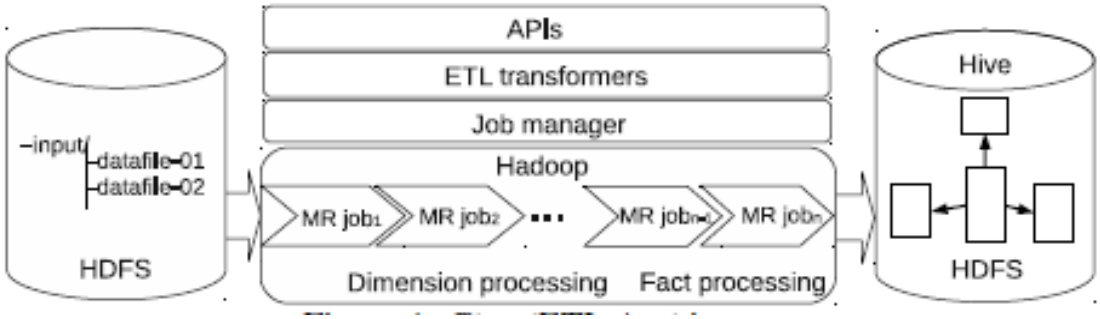


Figure 3: CloudETL Architecture (Liu et. al. 2014)

One of the key requirements for data processing using CloudETL is that the source data must reside in the HDFS. The workflow of CloudETL contains two sequential steps: dimension processing, and fact processing as shown in Figure 3. Despite the fact that CloudETL has

applied parallelization with the help of Hadoop and Hive, it lacks a visual interface for drawing the work flow. CloudETL architecture also lacks integration of machine learning tools which is increasingly becoming relevant for processing Big Data. Apart from parallelization, there are a number of other aspects that cloud based ETL currently are expected to support. These include support for easily scheduling data cleaning jobs, adding and removing data cleaning rules, integrating on-premises data with the data in cloud before processing, and leveraging machine learning tools to exploit relevant algorithms. CloudETL seems to have failed in highlighting these key aspects of cloud based ETL.

2.2 Data quality management

In data processing, one of the first and most important tasks is to verify data and ensure its correctness (Hamad & jihad 2011; Maletic 2000). Incorrectness in data can be caused by several reasons; for example, a device generating telemetry data can produce incorrect data due to programming error in the application installed on the device that generates data. Merging data from two sources can also cause incorrectness in data. The incorrect data values are commonly referred to as dirty data (Ananthakrishna et al 2002). A data value can be considered as dirty data if it violates an explicit statement of its correct value or if it does not conform to the majority of values in its domain (Chiang & Miller 2008). Identifying dirty data can be both an easy as well as a tedious task. It is easy to identify inconsistent and clearly erroneous values. For example, it is easy to identify negative values for *ChargeTime* in telemetry datasets of a mobile device. One can look into datasets and compare *chargeTime* and increased percent of battery for that *ChargeTime* to see if the increased percent contains negative value. Knowing most of the rows in datasets hold positive value for *chargeTime*, one can easily capture negative values as inconsistent values. However, it is often difficult to disambiguate inconsistent values that are potentially incorrect. For example, telemetry datasets of a mobile device shows decrease of battery capacity by fifty percent after charging phone for one hour because this could be possible if the consumption of battery during that charging time is greater than charge gain. In data quality management, several data cleaning rules are applied to identify and fix such errors in data.

2.2.1 Advantages of cloud technologies in data quality management

Writing custom services for Big Data integration often accounts for a major financial investment especially when data comes from various sources in various size and formats. Further, maintaining these services requires additional cost and effort. It would not be wrong to say that at some point handling Big Data with custom written services on proprietary infrastructure is if not impossible, certainly not cost-effective. This is where cloud computing is of great help. As pointed out by (Klinkowski 2013) the current expansion of the cloud computing follows a number of recent IT trends starting from "dot-com boom" to all the way to popularity, maturity, and scalability of the present internet. Also, the presence of large data centers developed by Google, Amazon, and Microsoft has made a huge contribution to cloud computing. Cloud computing can make better use of distributed resources and solve large-scale computation problems by putting the focus of thousands of computers on one problem (Sadiku 2014; Marinos & Gerard 2009). One of the key benefits of a system built on cloud technologies is that it is highly scalable. This is quite essential for the data quality management system that this thesis work aims to propose as scalability is a key requirement. There are a number of advantages that cloud computing offers including On-demand self-service, ubiquitous network access, location independent resource pooling, cost reduction, scalability, and transfer of risks (Sadiku 2014; Davenport 2013; Zhang 2010; Armbrust et al. 2010; Wang et al. 2010).

Cloud computing is heavily driven by ubiquity of broadband and wireless networking, falling storage costs, and progressive improvements in internet computing software (Dikaiakos et al 2009; Pearson et al 2009). In addition, systems built on cloud technologies have better speed, performance, and ease of maintenance. As (Grossman 2009) argues, most of the current cloud services are based on "Pay as you go" business model. This business model offers several benefits including reduced capital expense, a low barrier to entry, and ability to scale as demand requires. Grossman (2009) further points out that cloud services often enjoy the same economies of scale that data centers provide. For this reason, the unit cost for cloud based

services is often lower than if the services were provided directly by the organization itself. This thesis aims to build an ETL system for data quality management that fits well to Big Data scenarios. Consequently, it clear that the system must be built using cloud technologies. The rcently announced cloud based service of Microsoft Azure namely ADF can be used to connect with other storage, and compute services available on the Azure platform to build a scalable and reliable data quality management system. Section 2.6 discusses ADF to explore if a scalable, reliable, easy to maintain and monitor, and high performing data quality management system can be built around ADF by integrating other data services available on Azure platform.

2.2.2 Azure Data Factory (ADF)

Microsoft Azure defines ADF as a fully managed service for composing data storage, processing, and movement services into streamlined, scalable, and reliable data production pipelines. ADF service allows semi-structured, unstructured, and structured data of on-premises and cloud sources to be transformed into trusted information. The data landscape for enterprises is growing exponentially in its volume, variety, and complexity. As a result, data integration has become a key challenge. The traditional way of data integration is heavily concentrated on ETL process. The ETL process allows extracting data from various data sources, transforming the data to comply with the target schema of an Enterprise Data Warehouse (EDW), and finally loading the data into the EDW. Figure 4 depicts the ETL process.

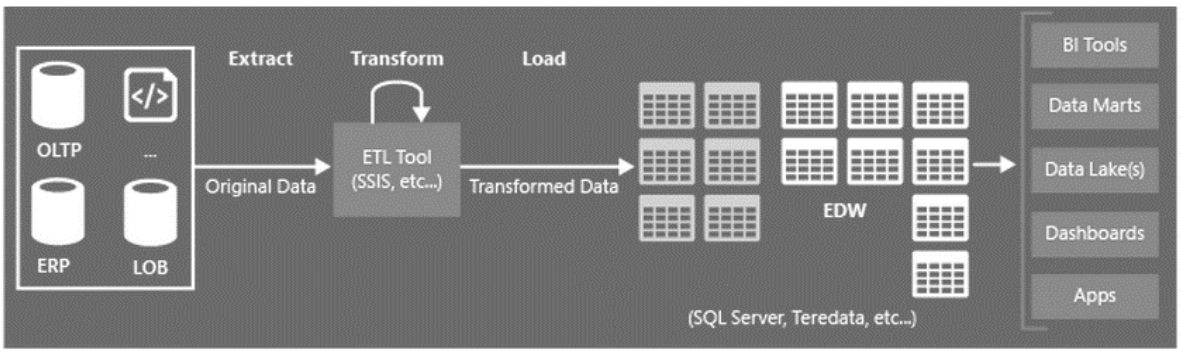


Figure 4: Traditional ETL process (Azure Microsoft, 2014)

Currently, data processing needs to happen across the geographic locations with the help of both open source and commercial solutions as well as custom processing services. This is needed mainly due to the growing volume, diversity, and complexity of data. For example, in current business set ups, enterprises mostly have various types of data located at various sources. This leads to challenges to connect all the sources of data and processing such as SaaS services, file shares, FTP, and web services. The next challenge in such cases is to move the data for subsequent processing when needed. Building custom data movement component or writing custom services to integrate these data sources requires a substantial financial investment and additional maintenance costs. Data factory solves these challenges by offering a data hub. The data hub can collect data storage and processing services and then it can optimize computation and storage activities. Currently, only HDInsight is supported as data hub. Data factory also provides unified resource consumption management and service for data movement when needed.

Data hub, as mentioned above, empowers enterprises for data sourcing from heterogeneous data sources. However, transforming such huge and complex data is another challenge that data integration processes need to address. Data transformation through Hive, Pig under Hadoop clusters can be very common especially when dealing with a large volume of data. To address the challenge of data transformation, data factory supports data transformation through Hive, Pig, and custom C# in Hadoop. In addition, ADF provides flexibility to connect information production systems with information consumption systems to cope with the changing business questions. Streamlined data pipelines are used to connect these systems in order to provide up-to-date trusted data available in easily consumable forms.

ADF has three stages in information production: (1) connect and collect; (2) transform and enrich; and (3) publish. ADF can import data from various sources into data hubs during its connect and collect stage. Processing of data takes place in the stage of transform and enrich. Finally, in the publish stage, data is published for BI tools, analytics tools, and other applications. Figure 5 shows the application model of ADF.

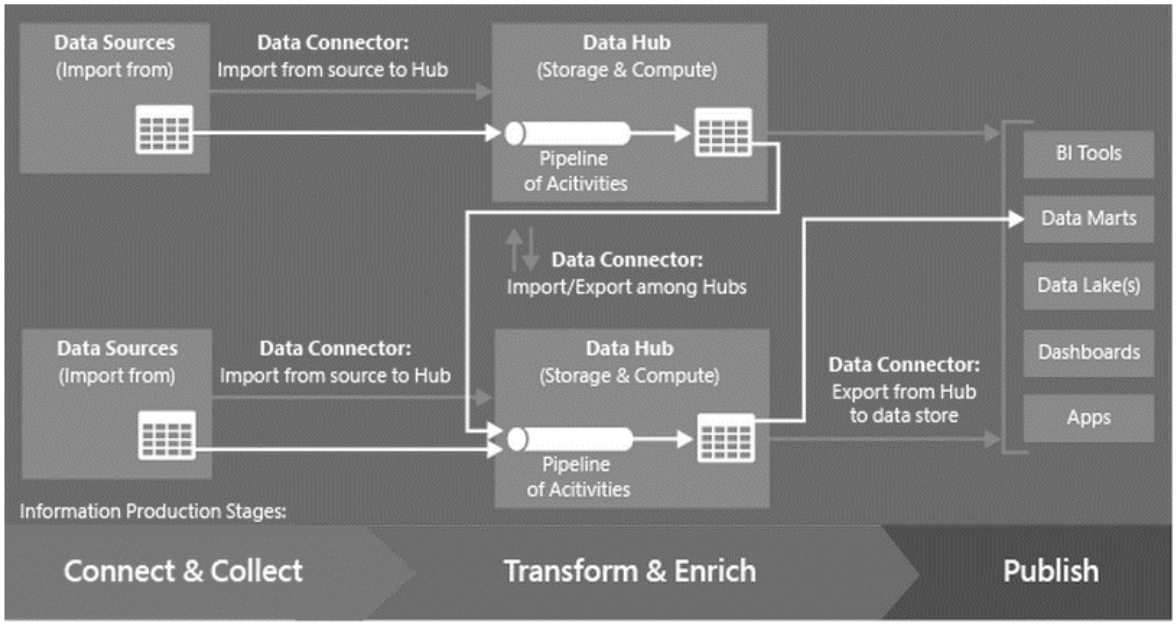


Figure 5: Application model of Azure data factory. (Azure Microsoft, 2014)

2.2.3 Data Pipeline

As defined by Azure Microsoft (2014), data pipelines are groups of data movement and processing activities that can accept one or more input datasets and produce one or more output datasets. Data pipelines on Azure data factory can be executed once or can be scheduled to be executed hourly, daily, weekly, or monthly. Amazon Web Services (AWS) seems to be one of the key competitors of Azure Microsoft. AWS defines its data pipelines as a service that can be used to automate the movement and transformation of data. AWS

data pipelines allow defining data-driven workflows where tasks can be dependent on the successful completion of previous tasks (Amazon web services 2014).

Data pipelines on Azure Microsoft and AWS appears to serve the identical purpose where feeding output of one task into the input of another task is very typical. Both these cloud platforms strongly focus on automation of data movement and processing. Azure data pipelines process data in the linked storage services by using linked compute service. Some of the key features that Azure data pipelines provide are: defining a sequence of activities for performing processing operations. E.g., copyActivity can copy data from source storage to the destination storage, hive/pig activities can process data using Hive queries or Pig scripts over Azure HDInsight cluster; scheduling. E.g, pipeline can interpret the active period to follow the duration in which the data slice will be produced;

AWS data pipelines facilitate integration with on premise and cloud storage system. These pipelines enable developers to use data in various formats on demand. Some of the key features that AWS data pipelines provide are: defining dependent chain of data sources, destinations, and predefined or custom data processing activities; scheduling processing activities such as distributed data copy, SQL transform, MapReduce applications, custom scripts against destinations including Amazon S3, Amazon RDS, or Amazon DynamoDB; running and monitoring processing activities on highly reliable and fault tolerant infrastructure; built-in activities for common actions such as copying data between Amazon Amazon S3 and Amazon RDS; running a query against Amazon S3 log data.

Figure 6 demonstrates a typical example of how web server logs can be scheduled to be stored in Amazon S3 on daily basis and then run a weekly Amazon Elastic MapReduce (Amazon EMR) cluster over the logs to generate traffic reports by using AWS data pipeline.

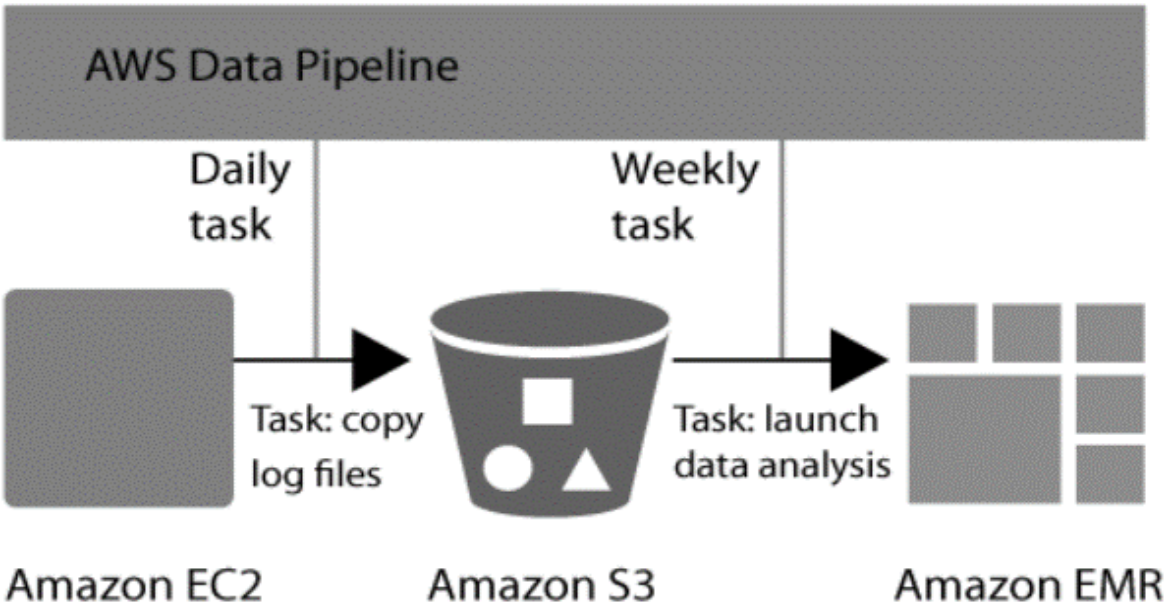


Figure 6. AWS data pipeline activities (Amazon web service, 2014)

AWS Data pipeline can be accessed through a web based console called AWS data pipeline console. AWS also provides command line tools and API to access and automate the process of creating and managing pipelines. These tools include AWS Command Line Interface, AWS Data Pipeline Command Line Interface, AWS Software Development Kits (SDK), and Web Service API. AWS Data pipelines consist of three main components: (1) Pipeline definition, (2) AWS Data Pipeline web service, and (3) Task Runner. Pipeline definition specifies business logic of data management such as input and output locations, activities, schedule, preconditions and so on. Preconditions are conditional statements that must be run before an activity can run. Preconditions are useful when for instance checking whether source data is present before allowing pipeline activity to attempt to copy it. AWS Data Pipeline web service interprets the definitions in the pipeline and assign tasks to workers to

move and transform data. The Task Runner polls the AWS Data Pipeline web service for tasks and then performs those tasks. As shown in Figure 6, Task Runner copies log files to Amazon S3 and then launches Amazon EMR clusters.

As Azure data factory supports data transformation through Hive, Pig, and custom C# processing in Hadoop, it allows the MapReduce pattern to parallelize data transformation which can automatically scale when data grow. Hive and Pig generate MapReduce functions and run them behind the scenes to carry out the requested query. Table 1 presents features comparison between the AWS and Azure data pipelines. The pricing associated with ADF based ETL is discussed in Section 5.5.

Table 1: Basic features comparisons between AWS and Azure Data pipelines

Features	**Azure**	**AWS**	**Alternative**
Dependent chain of data source	✓	✓	
scheduling pipeline activities	✓	✓	
running and monitoring activities	✓	✓	
Built-in activities common action such as copying data from storage system of own platform	✓	✓	
Creating pipelines from portal	×	✓	Azure PowerShell

Chapter 3

Implemented Data Factory for data quality management

In this Chapter, the architecture implemented for data quality management is described. This Chapter explains how Azure Data Factory (ADF) can be used to build a robust, automated, and scalable ETL system leveraging parallel processing and machine learning. The proposed ADF for data quality management system works in the following set up. Raw data is stored in Azure Blob store, Hadoop clusters provided by HDInsight and Hive scripts are used for data processing, Azure ML studio is used for applying statistical function by running custom R scripts. Finally, the cleaned data is stored in MS SQL database. A brief description of how an ADF project for data quality management was built and deployed is presented. This includes the description of the processes of integrating storage and compute service with ADF, setting data cleaning rules, and scheduling the data pipeline to perform data cleaning and data movement tasks. Some code snippets are shown to describe technical aspects of the implementation.

The implemented architecture supports performing a number of tasks such as picking raw data from Azure Blob Store, processing the raw data using Hadoop clusters and hive scripts, processing data via a web service provided by Azure Machine Leaning Studio (ML Studio), and moving data from Azure Blob store into Azure MS SQL. In short, the key components of the proposed architecture are ADF, Azure storage, HDInsight, ML Studio, and MS SQL. Section 3.1 through 3.3 describe these components in detail and explains how these components fit in the proposed architecture for data quality management. Section 3.2 presents the diagram views of the proposed architecture and give a brief description of some of the code snippets taken from the deployed data quality management systems built around the proposed architecture. Detailed descriptions of how sample data was processed using this architecture are presented in Chapter 4. The major components of the ETL are discussed individually before presenting the complete architecture. The proposed architecture is discussed in Section 3.2.

3.1 Creating ADF

As discussed in Section 2.2.2 ADF plays a central role in creating ETL system on Azure platform. ADF helps connect required components of ETL such as Azure blob for storing raw telemetry data, HDInsight for parallel data processing (cleaning), and ML Studio for applying machine learning models against the raw data, and SQL database for storing the cleaned data. This is why, creating the ADF pipeline is the very first step towards building the complete architecture of the ETL.

Creating and deploying ADF requires an Azure account. There are several purchase options available to get one (Purchase options for Azure Account 2014). During this thesis work, MSDN subscription was used. ADF can be created either from Azure preview portal or by using Microsoft Azure PowerShell. Creating ADF also requires defining a ResourceGroup for the ADF. Azure PowerShell has a command line interface that supports commands related to ADF. Some of the actions such as creating and scheduling pipelines cannot be performed through Azure preview portal. For such actions, Azure PowerShell can be used. However, making Azure preview portal independent so that all the actions can be performed through azure preview portal itself would be a big advantage.

ADF consists of two key components: linked services and pipelines. These components enable ADF to connect with other services and run scheduled jobs. Linked services help to connect other services available on Azure platform with ADF. Once these services are connected to ADF via linked services, pipelines can be scheduled to perform certain tasks including processing data or moving data from one source to another. The first step however is to create ADF. Next, creating linked service, pipelines, and scheduling pipelines follow respectively. For example, once ADF is created, it can be linked with Azure Blob Store and MS SQL and then a pipeline can be created to copy data from Azure Blob to MS SQL.

Further, to automate this data movement, the pipeline can be scheduled to perform this task of copying data from Azure Blob to MS SQL daily at a given time.

The linked service can be created either from graphical interface (Azure preview portal) or Azure PowerShell which is a command line interface. However, Azure preview portal only supports creation of linked services for Azure Storage account, Azure SQL, and SQL Server. Scripts should be written in JSON and should be uploaded to ADF using Azure PowerShell to create linked services for HDInsight or Azure ML Studio. HDInsight and ML Studio are covered in Section 3.1.2 and 3.1.3 respectively. As this thesis work aimed to propose an architecture for data quality management system built around ADF and other services available on Azure platform. The key services that were found to be promising and were used to construct the architecture for data quality management system are discussed in Section 3.1.1 through Section 3.1.4.

3.1.1 Windows Azure Storage

Windows Azure Storage (WAS) is a scalable cloud storage (Calder et.al 2011) that provides cloud storage. Data can be stored in the form of containers (blobs), tables (entities), queues (messages), and shares (directories/files) in WAS (Azure Storage 2015). WAS is massively scalable, durable, and highly available in nature. For this reason, WAS fits well to Big Data scenarios and hence it fits for the architecture this thesis work aims to propose. A standard storage account provides unique namespace for storage resources including Blob, Table, Queue, and File storage. The sample telemetry data used in this thesis work was in the form of text file which was suitable for storing in Azure Blob. Using the storage account, a Blob container was created and sample data was uploaded there. ADF also allows to keep the hive script in Azure Blob. The Hive scripts for processing the raw data (sample telemetry data) was also stored in Blob.

3.1.2 Azure HDInsight

Azure HDInsight is a framework for Microsoft Azure cloud implementation of Hadoop (Sarkar 2014). HDInsight includes several Hadoop technologies. To name a few, HDInsight includes *Ambari* for cluster provisioning, management, and monitoring; *Avro* for data serialization for Microsoft .NET environment; *HBase* which is a non –relational database for very large tables, *HDFS*, *Hive* for SQL-like query; *Mahout* for supporting machine learning; *MapReduce and YARN* for distributed processing and resource management; *Oozie* for workflow management; *Pig* for simpler scripting for MapReduce transformations; *Scoop* for data import and export; *Strom* for real-time processing of fast, large data streams; and *Zookeeper* for coordinated processes in distributed systems (Microsoft Azure, 2015) Accessing a cluster usually means accessing a Head Node or a Gateway which is a setup to be the launching point for the jobs running on the cluster (zhanglab 2015). Clusters on HDInsight can also be accessed in similar fashion. HDInsight can be considered as fully compatible distribution kit of Apache Hadoop which is accessible as platform as service on Azure. As highlighted by the Sysmagazine (2015), one of the most noticeable contributions to apache Hadoop ecosystem are the development of Windows Azure Storage Blob (WASB). The WASB provided a thin interlayer to represent units of blob storage of Windows Azure in the form of HDFS cluster of HDInsight (Sysmagazine 2015.) Figure 7 illustrates the internal architecture of HDInsight cluster.

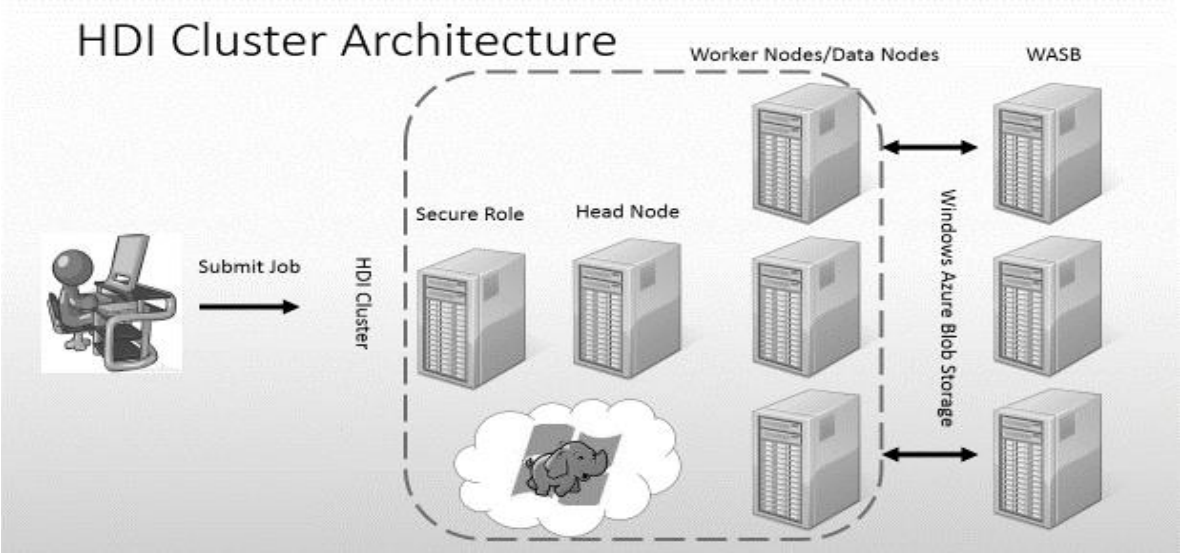


Figure 7: Internal Architecture of HDInsight cluster (Sysmagazine 2015)

As illustrated by Figure 7, a job has to pass through Secure Role first. Secure Role are responsible for three main tasks: 1) authentication, 2) authorization, and 3) giving finishing points for WebHcat, Ambari, HiveServer, HiveServer2 and Oozie on port 433. Head Node works as a site presented by virtual machines of level of Extra Large (8 kernels, 14 GB RAM) and fulfils the key function of Name Node, Secondary NameNode, and JobTracker of Hadoop cluster. Worker Nodes work as sites presented by virtual machines of level of Large (4 kernels, 7 GB RAM). Worker Nodes start tasks that support scheduling, execution of tasks and data access. WASB is in the form of HDFS. It is the default file system for HDInsight (Sysmagazine 2015.) As a result, HDInsight can access the data stored in Azure storage.

ADF can be linked to HDInsight in order to process data by running *Hive/Pig* scripts or MapReduce programs. For the ETL process, this enables programmers to schedule data cleaning jobs through ADF's pipelines that can process data by running Hive/Pig scripts or MapReduce program in HDInsight clusters. During this thesis work, Hive scripts were used to perform data cleaning in the HDInsight clusters. Hive facilitates querying and managing large datasets residing in distributed storage (Apache Hive 2015). Since Hive runs on top of MapReduce and has syntax very much like SQL, it eases programmers' life who prefer SQL like query language over MapReduce. For this reason, Hive was chosen for this thesis work.

However, the implemented ADF is not limited to *Hive*. During the data cleaning process, the cleaned datasets were stored back in the Azure Blob store so that other data cleaning rules can be applied if need.

3.1.3 Azure ML Studio

A number of publications in the area of Big Data analysis highlight the applicability of machine learning: "Developing and testing machine learning architecture to provide real-time predictions or analytics for Big Data" (Baldominos & Albacete & Saez & Isasi 2014), "A survey on Data Mining approaches for Healthcare" (Tomar & Agarwal 2013), "Big Data machine learning and graph analytics" (Huang & Liu 2014) and many more. Mining Big Data usually requires various technical approaches that include database system, statistic, and machine learning. Therefore, the ETL system designed to work in the Big Data scenarios should support these technical approaches. Machine learning is one of the most important applications of Big Data.

To support machine learning in the ETL process, the implemented data factory for data quality management proposed in this thesis work, integrates Azure ML Studio. Azure ML Studio is a recently announced (July, 2014) Machine Learning service of Microsoft Azure. ML Studio is a collaborative visual development environment that allows building, testing and deploying predictive analytics solutions as web service. ML Studio as shown in Figure 8 below can read data from various sources and formats.

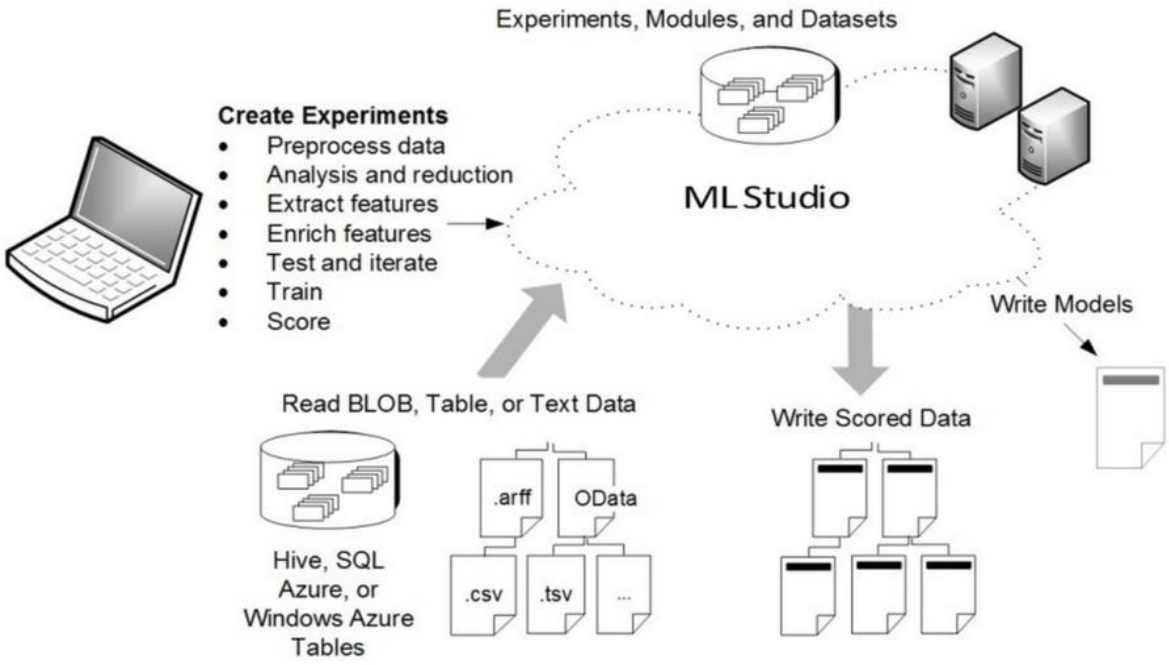


Figure 8: Overview of Azure ML Studio (Microsoft Azure 2015)

Azure ML Studio allows to extract data from various sources and transform and analyze that data through a number of manipulation and statistical functions in order to generate results. Azure ML Studio provides interactive canvas where datasets and analysis modules can be dragged- and dropped. There are several data transformation functions, statistical functions and machine learning algorithms available in ML Studio. These include Classification, Clustering, and Regression, Cross Validate Model, Evaluate Model, Evaluate Recommender Model, Assign to Cluster, Score Model, Train Model, Sweep Parameters and many more. In addition, custom R scripts can be run against datasets. A custom R script was used to calculate confidence interval during this thesis work. The R script is presented in Section 3.1.4. Figure 9 shows the experiment created for calculating confidence interval from a sample data stored at Azure Blob store. The experiment was then published as web service and tested.

Figure 9: Experiment created and published as web service for calculating confidence interval

Figure 9 can be read in four main steps. Each step is represented by a component of ML Studio which was dragged from the tool-bar into the workspace and configured. Each component has input and output port for accepting data and outputting data. The arrows in the Figure shows where the input data for a component comes from and where the output goes. In the first step, the source data is read from Azure Blob store. Reading data from Azure blob can be done by dragging the Reader component from the tool bar to work space in ML studio and configuring the reader component for accessing the Azure blob store and files stored in there. Configuration requires Azure Blob store account credentials and path of the input file inside the Azure Blob container. In the second step the data type of a column containing missing value, is converted into double. This is required because ML Studio

requires the column type to be double before the missing values in it can be replaced with 'NaN'. ML Studio has a dedicated component for doing this task. In the third step, the missing values are replaced with 'NaN' by using available component. In the fourth step, 95 percent confidence intervals are calculated against the input data. For running R script against input data, ML Studio has a dedicated component which can be dragged into the work space which then gives input area for writing custom R script. Below is the R script that was used to calculate 95 percent confidence intervals.

```
   # Map 1-based optional input ports to variables
1  data.1 <- maml.mapInputPort(1) # class: data.frame
   #Create the matrix for output (as many rows as in the input file)
2  output.1 <- matrix(NaN, ncol=3, nrow=nrow(data.1))
3  output.1<-data.frame(output.1)
    #Check which rows involve missing OK.count or missing Reset.count –returns either true or false
    (boolean)
4  na.rows <- which (is.na(data.1$OK.count) | is.na(data.1$Reset.count))
    #Assign the row count to parameter n.rows --
5   n.rows <- nrow(data.1)
   #Create the set of rows to be scanned by binom.test function
6  scan.rows <- setdiff(c(1:n.rows), na.rows)
   #Create a loop that performs the test
7   for(i in scan.rows) {
8        bin.test <- binom.test(x=c(data.1$OK.count[i], data.1$Reset.count[i]),n=1, conf.level=0.95)
9         conf.int.i.estimate <- bin.test$estimate
10       conf.int.i.lower <- bin.test$conf.int[1]
11       conf.int.i.upper <- bin.test$conf.int[2]
12       output.1[i,] <- cbind(conf.int.i.estimate,  conf.int.i.lower, conf.int.i.upper)
13                          }
    #Add descriptive column and row names to the output matrix
14 colnames(output.1) <- c("Actual",  "CI.lower", "CI.upper")
15 rownames(output.1) <- data.1$Trial.id
16 maml.mapOutputPort("output.1");
```

3.1.4 Azure SQL Database

Azure SQL database version V12 provides complete compatibility with Microsoft SQL Server engine as claimed by Azure. This version of Azure SQL allows users to create databases from Azure preview portal (MightyPen 2015.) ADF provides linked service and pipeline supports to connect with Azure SQL and run pipelines. During this thesis work, Azure SQL was used to store the cleaned data. Azure SQL database was linked with ADF using linked service. Tables were created in Azure SQL database for each of the cleaned datasets. ADF's copyActivity was used to copy the cleaned data from Azure Blob store to Azure MS SQL database.

3.2 Proposed Architecture

Several steps were taken to ensure the reliability and validity of the architecture before making the proposition. The first step was to study, explore, and test the potential components independently. In the second step, all those components were connected to ADF one by one and tested. For example, firstly, sample data was placed in Azure Blob and a table was created in Azure SQL database and then both Azure Blob storage and Azure SQL were connected to ADF via linked service and a pipeline was run to copy the data residing in Azure Blob to Azure SQL database table. After this experiment was successful, tables and pipelines scripts were updated to address more requirements.

Then next step was to integrate HDInsight with ADF. This was essential for processing data using Hadoop cluster provided by HDInsight. HDInsight was connected to ADF in similar fashion as Azure Bob and Azure SQL database were connected. The *Hive* script required to run against the sample data to get desired output was stored in Azure Blob. When creating linked service for HDInsight, cluster size, the path for accessing the *Hive* script residing in Azure Blob were defined. Also, clusters were configured to be of type On-demand cluster to avoid unnecessary costs. ADF allows users to configure HDInsight via linked service in such a way that depending on the schedule of the pipeline, Hadoop cluster can be set up automatically. Further, when pipelines finish running, the cluster can be shut down

automatically. This can save a lot of cost especially when the pipelines are running once a day because often all the jobs can be finished within a couple of hours. The *Hive* scripts contained only a few data cleaning rules in the beginning. After this experiment was successful, the *Hive* scripts were refined and remaining data cleaning rules were added in sequential order. At this point, a highly robust, scalable, and reliable data quality management system had been built which could be used to clean massive amount of data. Since the data cleaning rules were applied in sequential order, it became quite modular and it was easy to add a new rule or drop existing ones without affecting the whole architecture. The final step was to add machine learning capabilities to this ADF.

During this thesis work, there was a recent update done in ADF by Azure which allowed to connect Azure ML Studio to ADF via linked service and also pipeline support was added. This was a great opportunity to add machine learning capabilities to the data quality management system being developed. The experiment discussed in section 3.1.3 and shown in Figure 9 was created and R script was run against sample data stored in Azure Blob to calculate CI. Further, the experiment was published as web service. Finally ADF was then connected to this web service utilizing the recent update made by Azure. Figure 10 shows the complete architecture of the proposed data quality management system.

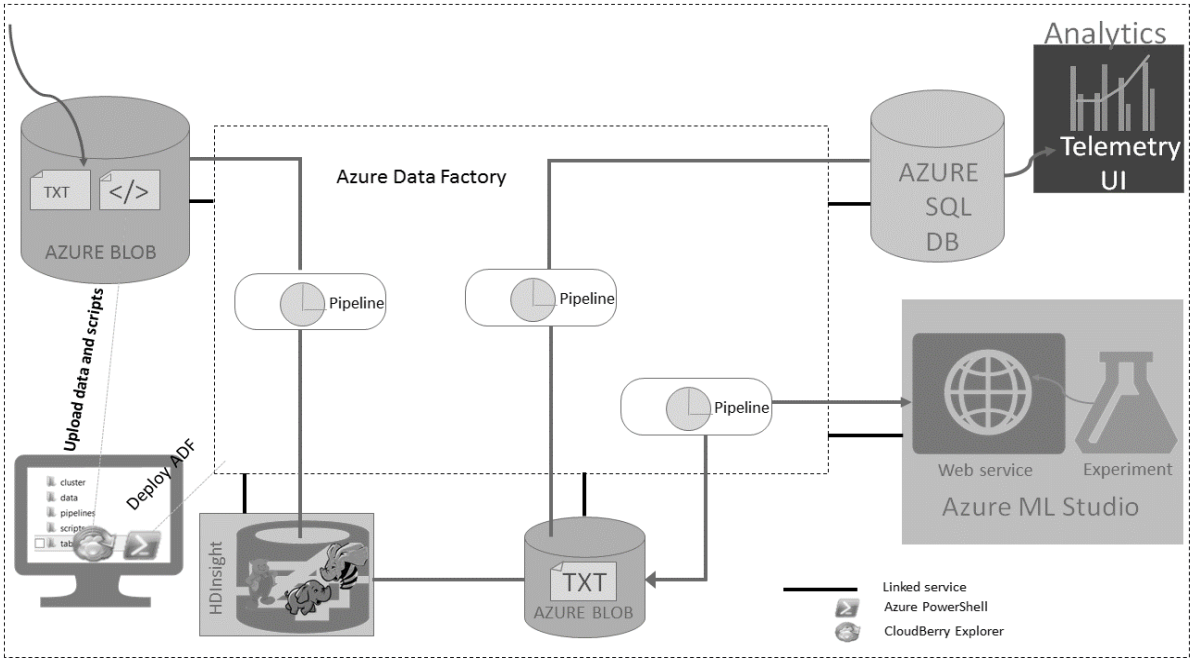


Figure 10: An architecture of implemented data factory for data quality management

As can be seen from Figure 10, first, pipeline picks raw data from Azure blob and processes the data in HDInsight clusters by running hive scripts. The results are stored in Azure Blob. Results are furthers transformed by using Azure ML Studio. The results are stored back in Azure blob in separate directory. Finally, the cleaned data is copied to Azure SQL database. The Telemetry UI reads data from Azure SQL database and presents them in various visual charts and tables.

In some cases, more than one service was found on Azure platform which could serve the same purpose. In such cases, the services which looked more current, scalable, and well-suited for ADF and business case of the client company, were chosen. For example, there was possibility to use *Mahout* for machine learning. However, the Azure ML Studio turned out to be easy to implement yet very powerful. For this, reason ML Studio was chosen over Mahout. Similarly *Hive* was chosen over *Pig* as the current database of the client company is MS SQL and developer of the case company showed more interest towards *Hive* than *Pig*. The reason was that *Hive*'s syntax is identical to SQL.

3.3 Deployment of the data quality management system

MSDN account can be used to get access to Azure preview portal which allows to create ADF and integrate other services such as HDInsight, Azure SQL database, Azure Blob store, and Azure ML Studio. However, only limited work such as creating ADF and linked services for MS SQL and Azure Storage can be done from the ADF preview portal. For the rest of the work including creating linked services for HDInsight, Azure ML Studio, creating pipelines, uploading input and output table schemas, scheduling pipelines are done by using *Azure PowerShell*. To upload raw data and *Hive* scripts in Azure Blob store, *CloudBerry Explorer for Azure Blob Storage* can be used.

Despite the fact that it is possible to create ADF and certain linked services from ADF preview portal, it is recommended to use an Integrated Development Environment (IDE). It is also more convenient to create a project and code all the components inside a single project

on the local machine than doing everything from the preview portal. This allows collaborating with other developers via version control. In addition, it makes it easier to maintain and update the ADF. During this thesis work, *Sublime Text 2* was used as IDE and Git was used as version control. Azure PowerShell can be used to deploy the tables, pipelines, linked services of ADF from local machine to ADF in the cloud. During this thesis work, ADF and linked services for Azure SQL, and Azure Storage were created from ADF preview portal and the rest were coded locally and deployed using Azure PowerShell. As an example, let us imagine we want to deploy a new pipeline named "batChargeTimeRule" which resides in a file called "batChargeTimeRule.json" on the local machine. Assuming the file is in current directory, the following command can be used to deploy the pipeline from local machine to ADF named "*TestDataFactory"* with ResourceGroupName *"TestResourceGroup"*.

```
1 New-AzureDataFactoryPipeline –ResourceGroupName TestResourceGroup -DataFactoryName
  TestDataFactory -File batChargeTimeRule.json
```

Figure 11 shows the diagram view of the final deployment of the implemented ADF that serves as the data quality management system. As a result of this deployment, we would now have a rule in place to remove battery charge data where the time taken to charge the device was much lower than would be physically possible.

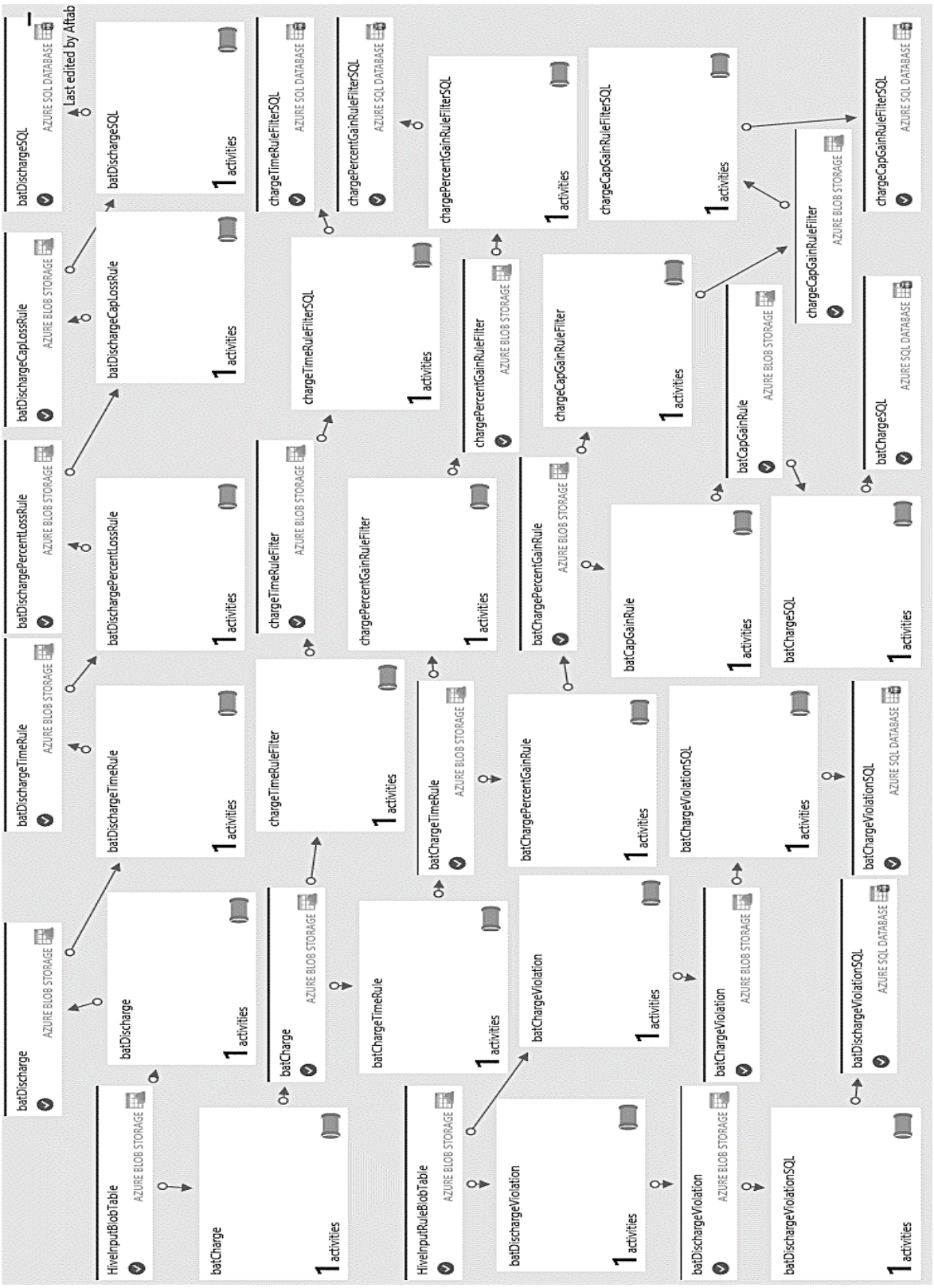


Figure 11: Diagram View of Implemented data factory for data quality management

ADF preview portal allows to visually see input/output tables and pipelines and visualize how data passes through different data cleaning rules and finally gets stored in SQL table. It is possible to see the table schemas and pipeline definitions by double clicking the table or pipelines. E.g., in Figure 11, *HiveInputBlobTable* is an on read table schema for sample data. A *batDischarge* pipeline takes that table as an input. The batCharge pipeline contains an activity which runs *Hive* scripts against the sample data inside *HDInsight* and creates batDischarge table. At this point only discharging events have been separated from the sample data and placed in *batDischarge* table. No data cleaning rule has been applied yet. Further, the next pipeline *batDischargeTimeRule* takes *batDischarge* table as input and its activity runs *Hive* script containing data cleaning rule that filters all the discharge time events where discharge time is 0 or negative and places the cleaned data in a table *batDischargeTimeRule*. Then, a pipeline *batDischargePercentLossRule* takes *batDischargeTimeRule* as input and applies data cleaning rule which filters out all the cases where percent loss contains negative value and places the cleaned data in *batDischargePercentLossRule* table. Later, another pipeline *batDischargeCapLossRule* takes *batDischargepercentLossRule* table as input and applies a data cleaning rule that filters out all the cases where battery capacity loss contains negative values and places the cleaned data in *batDischargeCapLossRule* table. Finally, as there is no other rule to apply, *batDischargeCapLossRule* table contains the final cleaned data and hence this table is copied to the Azure SQL table *batDischargeSQL* via another pipeline *batDischargeSQL*.

Below are sample code snippets that were used to connect with HDInsight and set up On-demand clusters. Sensitive information such as username, password etc. have been replaced by a placeholder and presented within angle brackets.

```
1  {
2      "Name": "MyHDInsightCluster",
3      "Properties":
4                  {
5              "Type": "HDInsightBYOCLinkedService",
6              "ClusterUri": "https://<clustername>.azurehdinsight.net/",
7              "UserName": "<Username>",
8              "Password": "<Password>",
9              "LinkedServiceName": "<Name of Linked Service>"
10                 }
11 }
```

Code snippet of linked service for connecting ADF to HDInsight

The code snippet shown above was used to connect to HDInsight and create a Hadoop cluster. The developer can choose username and password at this point when provisioning the cluster. It is advisable to give a meaningful cluster name and linkedServiceName. The next step is to configure clusters.

```
{
  "name": "HDInsightOnDemandCluster",
  "properties":
        {
            "type": "HDInsightOnDemandLinkedService",
            "clusterSize": "4",
            "jobsContainer": "adfjobs",
            "timeToLive": "02:00:00",
            "linkedServiceName": "<Name of Linked Service>"
         }
}
```

Code snippet of linked service for setting up On-demand clusters

In the above shown code snippet, the cluster is configured to be an On-demand cluster. On-demand cluster means, *HDInsight* will set up the cluster when the pipeline requires to run jobs. Once the jobs are finished, the cluster is shut down to cut the unnecessary costs. As can be seen, the cluster size was defined to be 4. This can be configured depending on the volume of the data which needs to be processed or can be left blank in which case *HDInsight* will decide the cluster size depending on the volume of the data given. *JobsContainer* is a container for example in Azure blob to accommodate all the MapReduce jobs and outputs. When using On-demand clusters, one might not want to shut down the cluster as soon as the job is finished so as to get some time to analyze the results and if needed tweak the Hive script and re-run the jobs (by running pipeline). This is important because *HDInsight* roughly takes about 20 minutes to set up the cluster and allocate the needed resources before it can run any data processing job. Once the cluster is set up and resource is allocated, running jobs only takes about a minute or two depending on the complexity of query and volume of data, and cluster size. Developer can set *timeToLive* so that when the job is finished, output can be analyzed and if needed Hive script can be tweaked and re-run the job without having to wait for another 20 minutes for *HDInsight* to setup cluster all over again. For this reason, *timeToLive* was set to be 2 hours as shown in the code snippet above. In the similar fashion, ADF can be linked with Azure SQL Database, Azure ML Studio.

As described in section 2.6.1 data pipelines are groups of data movement and processing activities that can accept one or more input datasets and produce one or more output datasets. Data pipelines can be executed once or can be scheduled to be executed hourly, daily, weekly and so on. Like linked services, pipeline definitions are defined in the JSON and uploaded to ADF via Azure PowerShell. Below is an example code snippet of a pipeline that takes *batCharge* as input and produces *batChargeTimeRule* as output by running *Hive* script against the input data.

```
{

"name": "batChargeTimeRule",
 "properties":
 {
    "description" : "It runs a Hive query and stores the result set in a blob",
  "activities":
 [
  {
       "name": "RunHiveQuery",
          "description": "Applies data cleaning rule that filters out chargtime < 1",
         "type": "HDInsightActivity",
          "inputs": [{"name": "batCharge"}],
         "outputs": [ {"name": "batChargeTimeRule"} ],
          "linkedServiceName": "HDInsightOnDemandCluster",
       "transformation":
         {
            "type": "Hive",
           "extendedProperties":
           {

                "RESULTOUTPUT":"wasb://<ContainerName>@<Storagename>.blob.core.windows.net/table
               s/battery/hiveoutput/chargingtable/batChargeTimeRule.txt",
             "Year":"$$Text.Format('{0:yyyy}',SliceStart)",
              "Month":"$$Text.Format('{0:%M}',SliceStart)",
              "Day":"$$Text.Format('{0:%d}',SliceStart)"
           },
           "scriptpath": "<ContainerName>\\scripts\\battery\\charging\\batChargeTimeRule.hql",
           "scriptLinkedService": "Name of the Linked Service"
         },
         "policy":
         {
           "concurrency": 1,
            "executionPriorityOrder": "NewestFirst",
            "retry": 1,
            "timeout": "00:30:00"
         }
       }
     ]
   }
 }
```

Code snippet of pipeline that runs hive scripts in HDInsight

In the given above code snippet, the type of the activity for this pipeline has been defined to be HDInsightActivity. The *HDInsightActivity* allows for the running of Hive scripts. The hive scripts can be stored in Azure Blob Store. The location of the hive script can be defined in the pipeline as *scriptpath* as shown in the code snippet above. The directory where the output is stored can be defined under *RESULTOUTPUT*. The *wasb* syntax is used to access Windows Azure Storage Blob which is followed by *ContainerName@StorageName.blob.core.windows.net/NameOfDirectory*. When this pipeline runs, it takes *batCharge* as its input table, sets up the OnDemand Cluster as defined under linkedServiceName, and runs the hive script picking it from location specified under *scriptpath*. The script performs data cleaning based on the rule defined in it and stores the output in *batChargeTimeRule* table and finally uploads the output table to the location specified under *RESULTOUTPUT*.

Chapter 4

Tested sample data

In this Chapter a brief description of the sample data used in this thesis work is given. Further, this Chapter introduces the identified data quality problems of the sample data of the client company and discusses how data cleaning rules were selected, applied, and assessed.

4.1 Sample data source

The sample data used in this thesis work is telemetry data of mobile devices particularly about battery. This data was made available by the client company. The data is captured as charging and discharging sessions through a feedback application installed on users' mobile devices. Whenever a user plugs in a phone for charging or disconnects a phone from charging, an event is generated. Charging and discharging events are identified by the value recorded under CycleType data field. For example, value 1 is recorded for charging events and value 2 is recorded for discharging events. Charging/discharging events not only record the current percentage of battery but also many other pieces of information about the device. E.g., charging events includes data including device id, charge time, charger type, percentage of battery that increased during the charging session, capacity of the battery, percentage of battery capacity that increased during the charging session, and battery temperature recorded at the end of the charging session. This is very valuable data for a company producing and selling mobile devices. This data can be used to measure the performance of the battery and enhance the user experiences by identifying the problem area and improving them.

To examine how false positives in automatic data cleaning can be minimized, this sample telemetry data was cleaned utilizing the data quality management system built based on architecture proposed in Section 3.2. Automation of data cleaning was achieved by implementing data pipelines provided by Azure Data Factory. For the purpose of validating the architecture, some of the known issues in the sample telemetry data were addressed in

data cleaning process. There were altogether 34 fields in the given sample. The relevant fields in the raw data which were used in the data cleaning process are shown in table 2.

Table 2: Relevant fields of the sample data used in analysis

Fields	Value	Explanations
cycleType	1 or 2	1 represents charging events and 2 represents discharging events
CycleResultCode	1 or 2	1 represents charging events and 2 represents discharging events
CycleTimeSeconds	Integer	If CycleType is equal to 1, then CycleTimeSeconds represents charging time else if CycleType is equal to 2 it represents discharging time
CycleBatteryStart_Pct	Integer	Represents battery % when charging started
CycleBatteryEnd_Pct	Integer	Represents battery % when charging stopped
CycleCapacityStart_mWh	Integer	Represents available battery capacity when charging started
CycleCapacityEnd_mWh	Integer	Represents battery capacity when charging ended
ClientSessionStartDateTime	DateTime	When charging/discharging started
ClientSessionEndDateTime	DateTime	When charging/discharging ended

4.2 Known issues in sample data

The sample data contained dirty data. This can partly be expected as batteries are physical objects which degrade in performance over time. There are also physical interfaces in the devices which may not work as well with some 3rd party provided batteries and lead to poor measurements. The client company gets this data on a daily basis and uses it for understanding a number of different aspects related to power consumption. For instance, the date helps understand battery performance against different firmware versions, charging behavior of users for example when people charge their phone more often, types of charger people mostly use and so on. The client company stores this data in a MS SQL database. The client company has a web portal that reads data from database and presents data in visual form such as graphs and tables. The client company is aware that only good quality data can lead to good decisions. Consequently, the client company performs data cleaning on daily basis to maintain the quality of data. However, this is a lengthy task as the volume of the data the case company gets is expected to grow massively in near future. This explains the need for automated data cleaning. The architecture proposed in this thesis work supports automated data cleaning and therefore can tackle this issue. The known issues in the sample telemetry data which were addressed during data cleaning are as follows:

- Charge time contains cases with negative value
- Discharge contains cases with negative value
- Referring to the above table 2, battery % gain for charge time is calculated by subtracting CycleBatteryEnd_Pct from CycleBatteryStart_Pct. For the scenario where a device consumes more battery than it gains from charging (E.g., when user is playing video game and Wi-Fi is turned), battery % gain is captured as negative value. So there are certain extreme scenarios where devices can be charging but are consuming power faster than they gain power via re-charging. However, it was captured during data cleaning process to observe how frequent such cases are.

- In some cases battery % increases with positive charge time but battery capacity does not increase. Capacity gain is calculated in similar fashion as battery % gain by subtracting CycleCapacityStart_mWh from CycleCapacityEnd.
- In some cases with positive charge time battery capacity increases but battery % gain does not increase
- Charge loss is negative. Charge loss is calculated subtracting CycleBattryEnd_Pct from CycleBatteryStart_Pct.

With the existing errors in the sample data listed above, it would be quite risky to make product related decisions as there is high risk of ending up making wrong decisions. For example, predicting the average battery life of a phone from datasets which contain such garbage data can result into a false positive. In their description of the problems that dirty data can cause when making decisions (Chiang & Miller 2008) warns that dirty data is a serious problem for business leading to incorrect decision making, inefficient daily operations, and ultimately wasting both time and money. Application of data quality rules (Chiang et. al 2008) is the common rule of thumb for identifying and cleaning dirty data from datasets.

For the selection of data cleaning rules, this thesis work adapted with the approach proposed by (Hoa & Chun 2008). This approach consists of five parts which are: (1) rules definition, (2) data quality problem definition, (3) cleaning results assessment, (4) rules performance storage, and (5) rules scheduling. Hoa (2008) advocates for speed when measuring rules performance. However, this thesis work also aims to measure the false positive rate of data cleaning rules when measuring the rules performance. This can help minimize the false positive rate of the data cleaning rules through multiple iteration. Figure 12 illustrates the adapted optimal cleaning rule selection model.

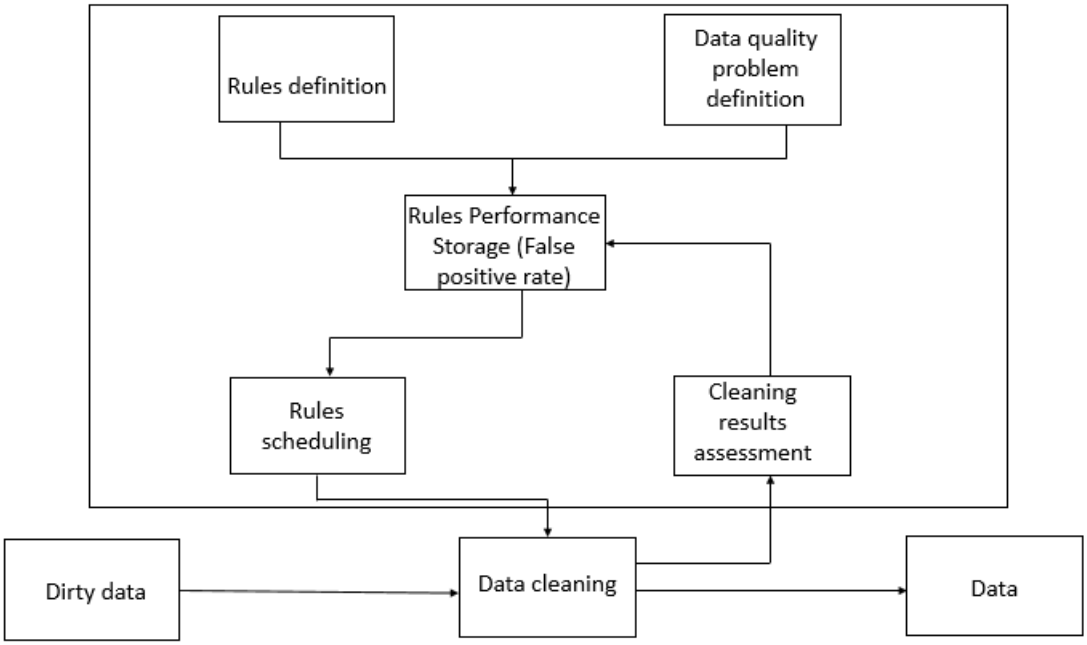


Figure 12: Optimal cleaning rules selection model (adapted from Hoa & Chun 2008)

To get an idea of how much data can be filtered out when data cleaning rules are applied for the known issues in sample data, two different tables '*batChargeViolation*' and '*batDischargeViolation*' were created in MS SQL database to hold % percent of data that each rule related to charging and discharging can filter. Then using the proposed architecture a pipeline was run which picked the sample data from Azure blob, ran the Hive script against it in *HDInsight*, and finally copied the results to '*batChargeViolation*' and '*batDischargeViolation*' tables of MS SQL. This was done for seven different sample datasets to observe how results changed over time. This gave a benchmark for evaluating potential data cleaning rules to address the known issues in the sample data. Table 3 shows the evaluated potential data cleaning rules, their description and the portion of hive script needed.

Table 3: Potential data cleaning rules for battery related telemetry data

Potential Data cleaning rules	Description	Hive script
Charge time rule	Calculates the total % of cases where charge time < 1 second	ROUND(SUM(CASE WHEN CycleTimeSeconds < 1 and CycleType=1 and CycleResultCode=1 THEN 1 ELSE 0 END)*100/SUM(CASE WHEN CycleType=1 and CycleResultCode=1 THEN 1 ELSE 0 END),2) AS ChargeTimeRule
Discharge time rule	Calculates the total % of cases where discharge time < 1 second	ROUND(SUM(CASE WHEN CycleTimeSeconds < 1 and CycleType=2 and CycleResultCode=2 THEN 1 ELSE 0 END)*100/SUM(CASE WHEN CycleType=2 and CycleResultCode=2 THEN 1 ELSE 0 END),2) AS DischargeTimeRule
Charge % gain rule	Calculates the total % of cases where charge % gain < 1	ROUND(SUM(CASE WHEN CycleType=1 and CycleResultCode=1 and (CycleBatteryEnd_Pct-CycleBatteryStart_Pct) < 1 THEN 1 ELSE 0 END)*100/SUM(CASE WHEN CycleType=1 and CycleResultCode=1 THEN 1 ELSE 0 END),2) AS ChargeGainRule
Charge % loss rule	Calculates the total % of cases where charge % loss < 1	ROUND(SUM(CASE WHEN CycleType=2 and CycleResultCode=2 and (CycleBatteryStart_Pct-CycleBatteryEnd_Pct) < 1 THEN 1 ELSE 0 END)*100/SUM(CASE WHEN CycleType=2 and CycleResultCode=2 THEN 1 ELSE 0 END),2) AS ChargeLossRule
Charge % gain error rule	Calculates the total % of cases where charge time > 0 and there has been capacity gain but not percent gain	ROUND(SUM(CASE WHEN CycleType=1 and CycleResultCode=1 and CycleTimeSeconds > 0 and (CycleCapacityEnd_mWh-CycleCapacityStart_mWh) > 0 and (CycleBatteryEnd_Pct-CycleBatteryStart_Pct) < 1 THEN 1 ELSE 0 END)*100/SUM(CASE WHEN CycleType=1 and CycleResultCode=1 THEN 1 ELSE 0 END),2) AS ChargePercentGainErrorRule
Capacity gain error rule	Calculates the total % of cases where charge time > 0 and there has been percent gain but not capacity gain	ROUND(SUM(CASE WHEN CycleType=1 and CycleResultCode=1 and CycleTimeSeconds > 0 and (CycleBatteryEnd_Pct-CycleBatteryStart_Pct) > 0 and (CycleCapacityEnd_mWh-CycleCapacityStart_mWh) < 1 THEN 1 ELSE 0 END)*100/SUM(CASE WHEN CycleType=1 and CycleResultCode=1 THEN 1 ELSE 0 END),2) AS CapacityGainErrorRule

Seven days results from both the tables are presented in Chapter 5. Figure 13 shows the results obtained from charge time and percent gain rules. Figure 14 shows the results obtained from discharge time and percent loss rules, and Figure 15 shows the results of percent gain error and capacity gain error rules.

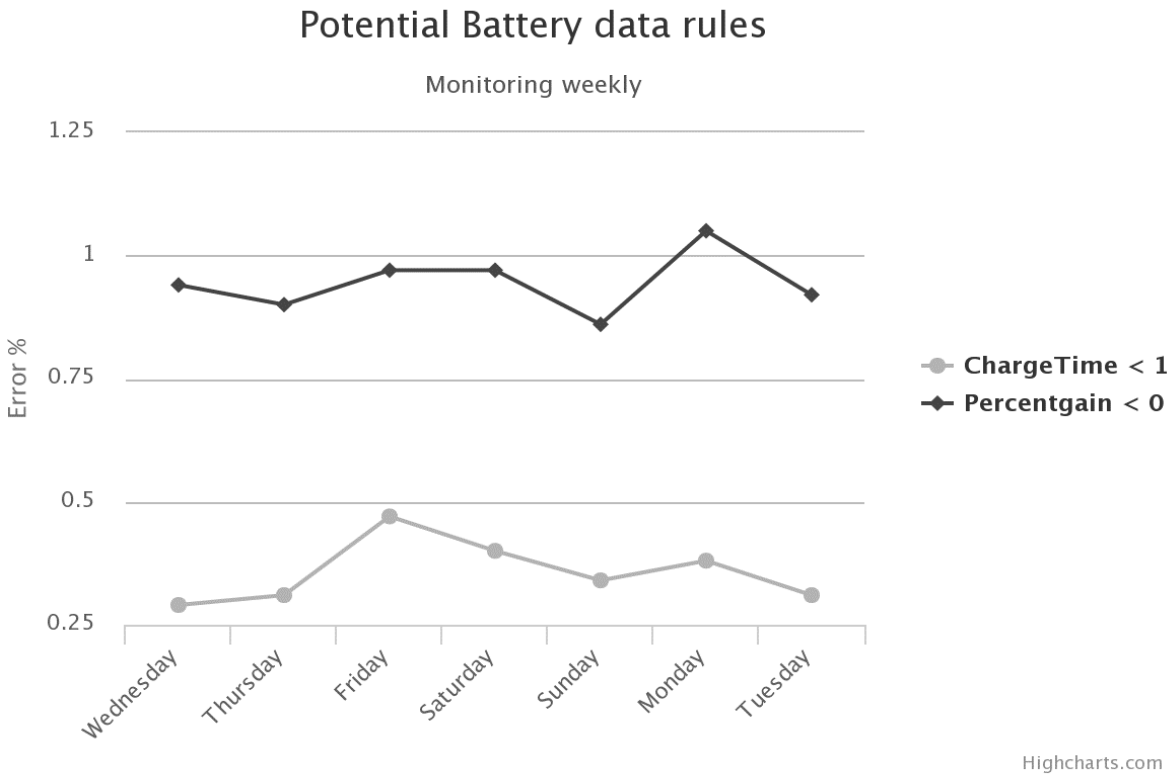


Figure 13: Seven days results of Potential charge time and Percent gain rules

As can be seen from the Figure 13, during the seven days period, total % of cases where charge time < 1 second is between 0.25% to 0.5 %. During the same period of time, the cases where charge percent gain < 0 is between 0.75% to 1.25%.

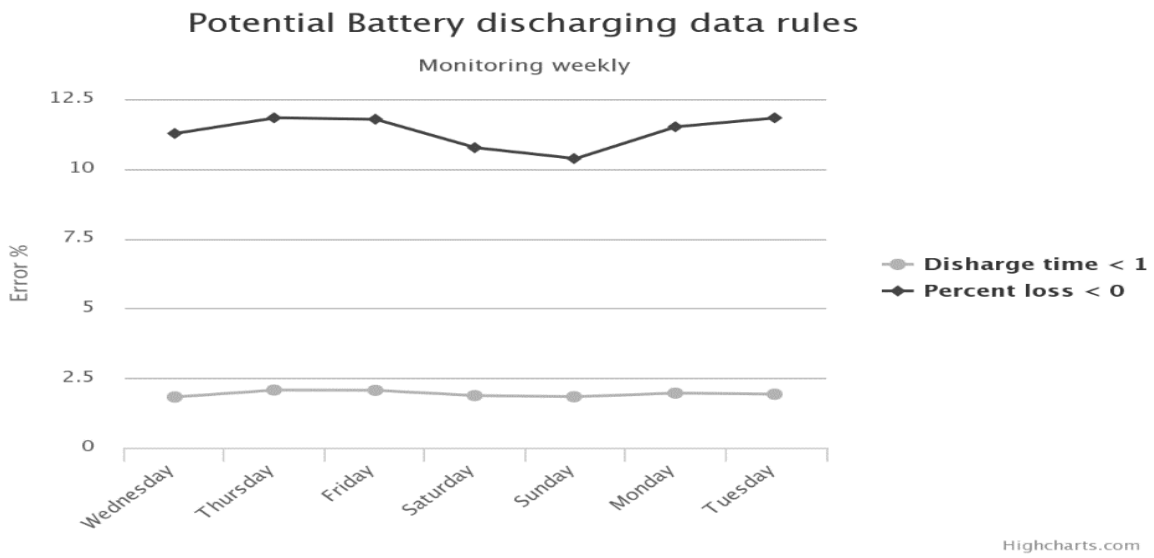


Figure 14: Seven days results of Potential discharge time and Percent loss rules

Figure 14 shows that cases discharge time rule has caught is below 2.5 %. Percent loss rule seems to be quite problematic. Applying percent loss rule in data cleaning can filter out about 12 % of total discharging data. Therefore, it would be wise to consider further evaluation of percent loss before deciding to apply it in data cleaning. For example, this could be happening due to some hardware problems or temperature of the phone.

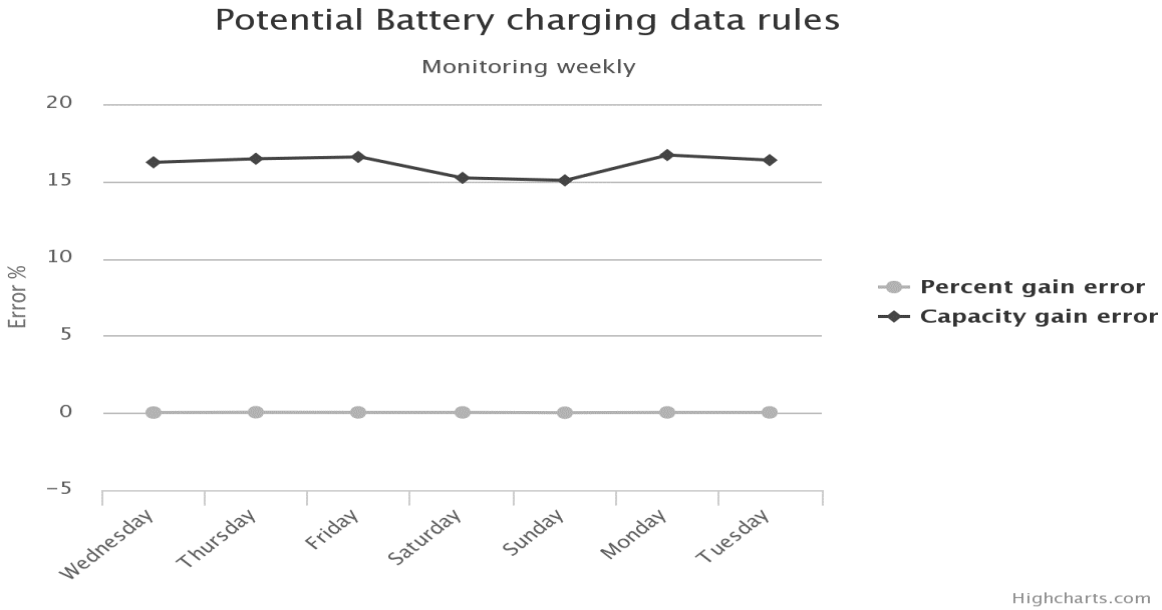


Figure 15: Seven days results of Potential percent gain error and capacity gain error rules

As shown in Figure 15, percent gain error is significantly nominal in comparison with capacity gain error. This figure points out a serious issue with capacity gain error. Referring to the description of capacity gain error presented in Table 3, capacity gain error rule calculates the total % of cases where charge time > 0 and there has been percent gain but not capacity gain. This issue with capacity gain error can cause false positives for example if included in calculating the total charge time required for a phone's battery to be fully charged. This figure also points out that using percent gain instead of capacity gain when predicting total time required for a phone's battery to fully charge is less risky.

4.3 Data quality problems and data cleaning rule definitions

Quality problems in the sample data were already known. Evaluating potential data cleaning rules against 7 days of datasets helped better understand the possible impact these rules can have. Observing the capacity gain error, it was clear that percent gain and capacity gain are out of sync. Applying a data cleaning rule to filter negative capacity gain can filter a significant amount of data. This was already an indication that percent gain should be preferably used over capacity gain when drawing any conclusion from the data. Data cleaning rules for charging and discharging events were defined based on the listed known issues of the sample data and the evaluation of the potential data cleaning rules. Further, these data cleaning rules were assigned a priority order for their sequential application. Priority order was assigned based on the amount of data a rule could potentially filter out. The rule that would filter the least amount of data got first position in sequential order of the rule. Using priorities for the cleaning rules helped to minimize the amount of data being lost when applying filters and this was important as more data gave better and reliable results. Table 4 shows the defined data cleaning rules and their priority order.

Table 4: Defined data cleaning rules and their priority orders

Data cleaning rules for charging events		
Data cleaning rules	**Description**	**Priority order**
ChargeTimeRule	Filters out charge events having charge time <=0	1
PercentGainRule	Filters out charge events having percent gain <0	2
CapacityGainRule	Filters out charge events having capacity gain <=0	3
Data cleaning rules for discharging events		
Data cleaning rules	**Description**	**Priority order**
DischargeTimeRule	Filters out discharge events having discharge time <=0	1
PercentLossRule	Filters out discharge events having percent loss <0	2
CapacityLossRule	Filters out discharge events having capacity loss <=0	3

4.4 Assessment of data cleaning rules

Assessment of the data cleaning rules was done against the performance of the rules. To assess the performance of the data cleaning rules, false positive rate was calculated for each of the applied rules. As suggested by Hoa (2008), the false positive rate can be calculated by counting the number of wrongly identified rows over total identified rows multiplied by 100. The same approach suggested by Hoa (2008) was used in this thesis. Further, the 95 percent confidence interval (CI) was calculated for each of the data cleaning rules to observe the possible variation in false positive rate when applying the rules to different sizes of datasets. Chapter 5 presents the process of defining the criteria for false positive and the process of calculating 95 percent CI.

Chapter 5

Results and Evaluations

In this Chapter, the results of running tests on the sample data are discussed. The sample data was tested on the ADF built during thesis work. Results obtained from the test helped in both verifying and quantifying the known issues of the sample data and evaluating the utility and reliability of the ADF itself. The results of individual data cleaning rules were evaluated to determine criteria for identifying false positives. Further, false positive rates for each of the data cleaning rules were calculated and quantified with 95 percent confidence interval. These data points were then used to figure out ways to minimize the false positive rate for the applied data cleaning rules. Figure 16 presents total charging and discharging events of the sample data.

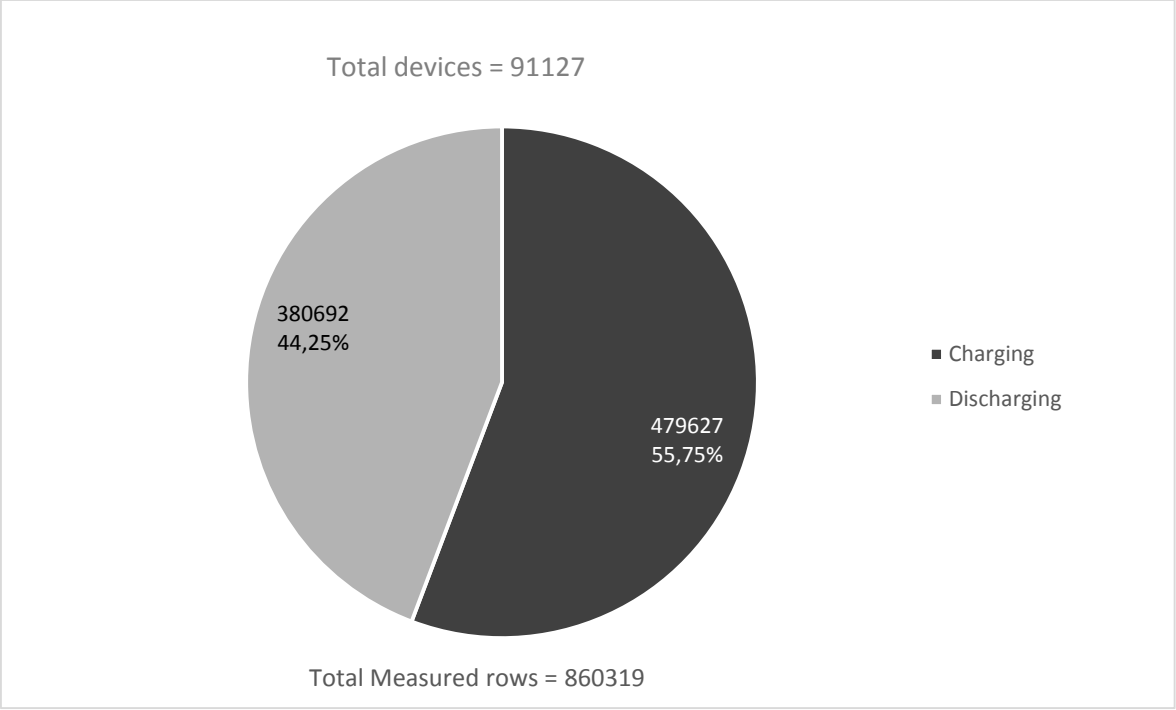


Figure 16: Percentage of Charging and Discharging rows

As indicated by Figure 16, there were a total of 91127 devices which contributed to this sample data. The total events captured were 860319. Out of these total rows, there were 479627 (55.75 %) charging events and 380692 (44.25 %) were discharging events. Charging and discharging events were expected to be 50-50. However, it was clear from these results that there was difference of about 5-6 %.

To address the known issues of the sample data, 3 data cleaning rules were applied in sequential order. Figure 17 presents the results showing the impact of data cleaning rules on charging data.

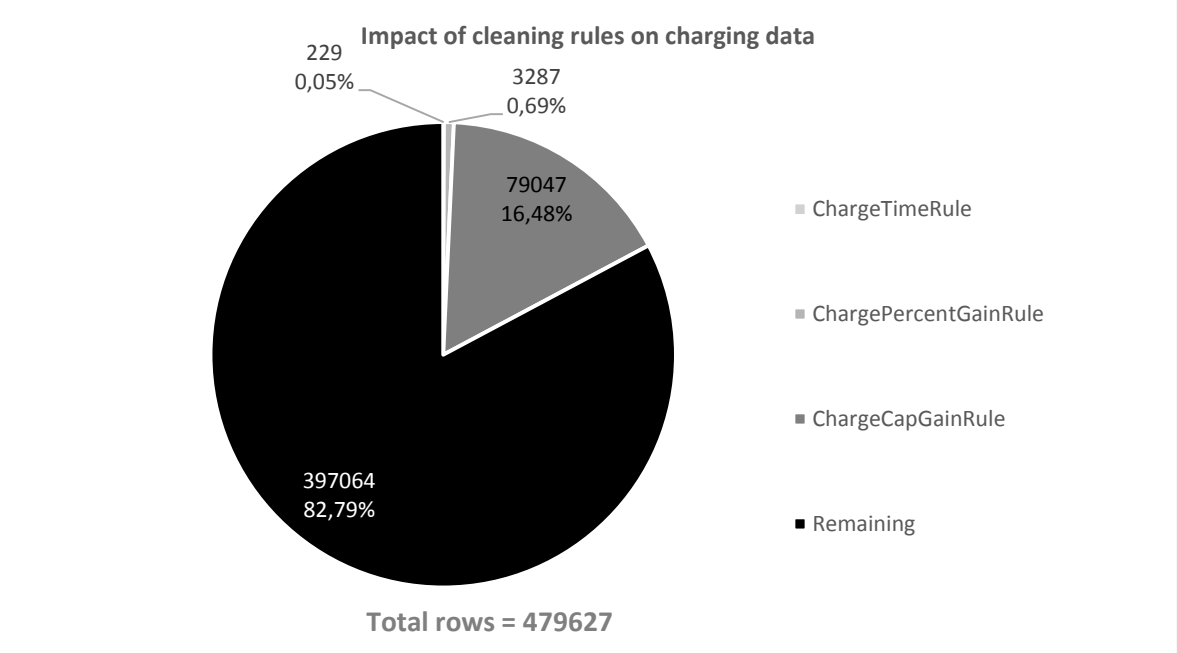


Figure 17: Percentage of filtered and remaining data after apply rules sequentially

The first data cleaning rule in the order was ChargeTimeRule. As can be seen from Figure 17, ChargeTimeRule filtered out 229 rows which was about 0.05 % of the total charging data. The second rule was CharePercentGainRule which filtered out 3287 rows that was 0.69% of the total charging data. Similarly the third rule, ChargeCapGainRule filtered out 79047 rows which was 16.48 % of total charging data. All the data that passed through these 3 rules were considered to be clean data shown as remaining data. As suggested by the figure above, about 18 % of total data was filtered out leaving 82 % of data as clean data. Figure 18 presents the impact of the data cleaning rules on discharging data.

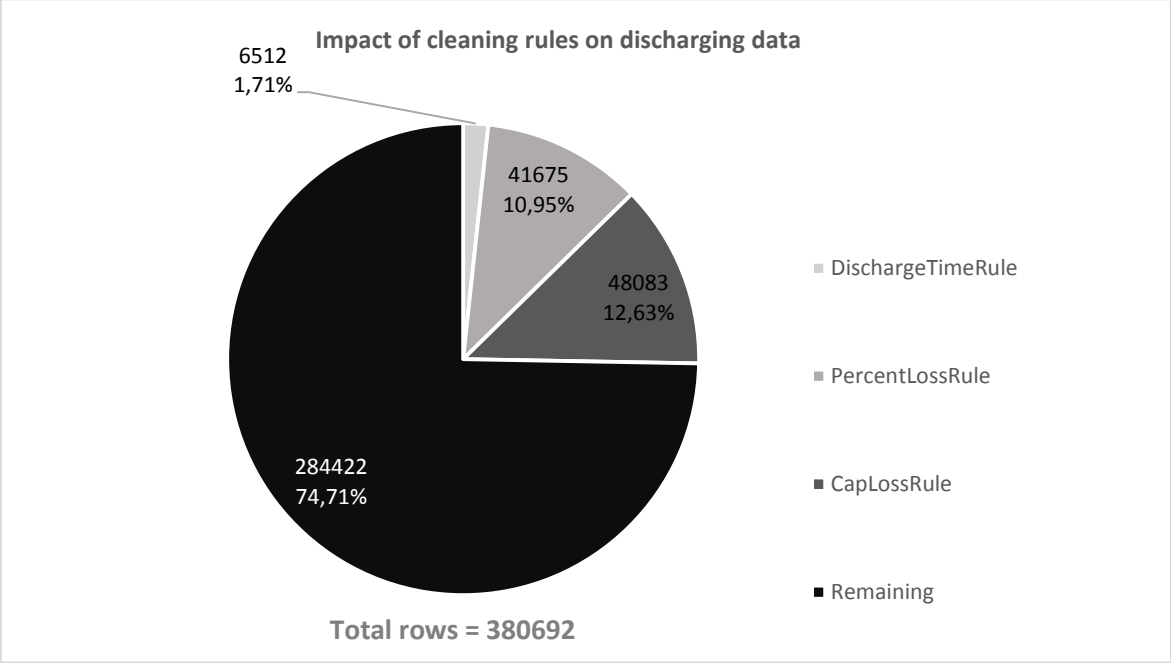


Figure 18: Percentage of filtered and remaining discharging data

For discharging data, the first data cleaning rule in the order was DischargeTimeRule. As can be seen from Figure 18, DischargeTimeRule filtered out 6512 rows which was about 1.71 % of the total discharging data. The second rule was PercentLossRule which filtered out 41675 rows that was 10.95% of the total discharging data. Similarly the third rule, CapLossRule, filtered out 48083 rows which was 12.63 % of total discharging data. All the data that passed through these 3 rules was considered to be clean data and is shown as remaining data. As suggested by the figure above, about 26 % of total data was filtered out leaving 74 % of data as clean data.

As mentioned in Section 4.2, one of the known issues in the sample data was that percent gain and capacity gain were out of sync. In other words, most of the time battery percent was increased against charge time. However, within the same event there was not any change recorded for battery capacity and vice versa. Figure 19 and 20 presents error rate of percent gain and capacity gain meaning how often percent of battery increased but capacity did not and vice versa. Further, the impact of charging events being extracted from raw data based

only on CycleType and with a combination of CycleType and ResultCode was also evaluated.

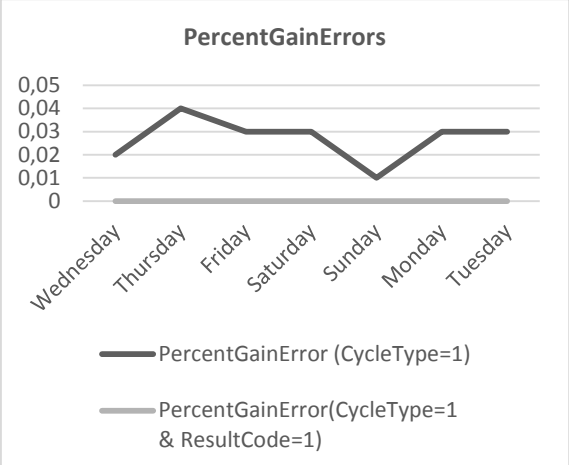


Figure 19: Percent gain error rate

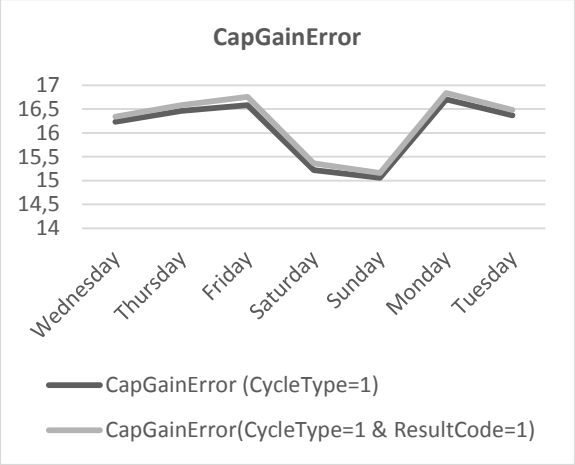


Figure 20: Capacity gain error rate

As indicated by Figure 19 and Figure 20, percent gain and capacity gain are out of sync. *ChargeTime* seems to impact *PercentGain* well enough with minor error between 0.01 -0.5 %. However, about 16% of the charging data does not seem to have any impact on *ChargeTime*. Further, the combination of CycleType and ResultCode decreased the *PercentGainError* to 0 %. Predicting the time required to fully charge a device can be based on battery *PercentGain* or *CapGain* and the *ChargeTime*. However, since 16% of the total charging data do not seem to have any impact on *CapGain*, predicting time required to charge a phone fully can be a wrong prediction. Therefore, choosing *PercentGain* instead of *CapGain* is certainly a better decision.

To calculate the false positive rate for each rule, an approach pointed out by Hoa (2008) was used. The following formula was used for computing false positive rate.

False Positive = (Number of wrongly identified rows by the Rule/ Total identified rows by the Rule)*100%

All the rows that were filtered out by each data cleaning rules were stored in a separate table. In the implemented ADF, while applying sequential data cleaning rule, also the garbage data was collected in separate table. Garbage data was collected in order to analyze how much of

good data was filtered out by the data cleaning rules. Further, garbage data was inspected manually and with help of SQL commands. A major advantage of cloud based cleaning approaches is that they are more scalable and setting up this kind of extra storage for garbage data is a very straightforward thing to do whereas in a more local environment, it might not be feasible to set up this kind of extra storage.

To calculate false positive rate, and confidence interval against the garbage data, various steps were taken. These steps include: defining criteria to identify false positive, running R script to calculate CI, and analyzing false positive rates and CIs and proposing ways to minimize false positives.

5.1 Defining criteria to identify false positive

ChargeTimeRule

Firstly, the criteria for determining wrongly identified rows was defined. It was observed that the average *PercentGain* per 10 minutes from the dataset when cleaned by rule *ChargeTimeRule* was about 7 %. This means on average mobile devices recharged about 42% of their battery capacity in one hour. Since *ChargeTimeRule* filtered out all the data having *chargingtime* equal to or less than zero, no row in the filtered data (garbage data) contained meaningful *chargetime*. However, it was possible to use *ClientSessionStartDateTime* and *ClientSessionEndDateTime* in order to calculate chargetime. Therefore, hourly *PercentGain* against *chargetime* calculated from *ClientSessionStartDateTime* and *ClientSessionEndDateTime* was used for determining the wrongly identified rows. Among the filtered (dirty datasets) obtained from *ChargeTimeRule*, all the rows that contained hourly *PercentGain* between 40 to 70 % were considered to be false positives. Out of 229 rows identified by *ChargeTimeRule*, a total of 3 rows were detected to be false positives.

False positive for ChargeTimeRule = (3/229) * 100 %

= 1.31 %

5.2 Confidence Interval (CI)

Defining the criteria for the wrongly identified rows and calculating the false positive rate give an impression of how good or bad the rule is. However, the probability of the data cleaning rules performing with the same false positive rate is uncertain. For example, it is difficult to predict that ChargeTimeRule will have same false positive rate when the rule is applied to a much larger dataset. To understand how frequently the same false positive rate can be achieved when this data cleaning rule is applied to different sized datasets, there must be an estimation of range values with a confidence level. In statistical analysis this can be achieved by calculating confidence interval (CI). In this thesis work, Clopper-Pearson interval method is used which is also known as 'exact' method. The Clopper-Pearson interval can be written as:

$$S_{\leq} \cap S_{\geq} \quad \text{or equivalently} \quad (\inf S_{\geq}\,,\, \sup S_{\leq})$$

with

$$S_{\leq} := \left\{\theta \middle| P\left[\mathrm{Bin}\left(n;\theta\right) \leq X\right] > \frac{\alpha}{2}\right\} \quad \text{and} \quad S_{\geq} := \left\{\theta \middle| P\left[\mathrm{Bin}\left(n;\theta\right) \geq X\right] > \frac{\alpha}{2}\right\},$$

where $0 \leq X \leq n$ is the number of successes observed in the sample and Bin(n; θ) is a binomial random variable with n trials and probability of success θ (Clopper & Pearson 1934). The 'exact' method has often been regarded as definitive as it eliminates both aberrations and guarantees strict conservatism. The coverage probability obtained by the 'exact' method is at least 1- α for all θ with $0 < \theta < 1$. It comprises all θ for which precisely computed, 'exact' aggregate tail areas are not less than α/2. (NewCombe 1998.)

Further, an R script was used to compute 95 percent CI for ChargeTimeRule. Since the proposed architecture allows us to run R scripts via Azure ML against datasets stored in Azure Blobs, R script is an appropriate approach for calculating 95 percent CI. Below is an example of the R script used to calculate 95 percent CI.

```
> binom.test(x=3, n=229, conf.level=0.95)

        Exact binomial test

data:  3 and 229
number of successes = 3, number of trials = 229, p-value < 2.2e-16
alternative hypothesis: true probability of success is not equal to 0.5
95 percent confidence interval:
 0.002709816 0.037805577
sample estimates:
probability of success
            0.01310044
```

As can be seen from the script above, there are three parameters. The first parameter is a number of success which in other words is a vector length of 2 giving the number of successes and failures, respectively. The second parameter which is number of trials which is ignored if the first parameter has length 2. The third parameter is confidence level for the returned CI. CI shown above means that we are 95% sure the false positive rate will be in range 0.2-3.7%. False positive rate and the CI for data cleaning are summarized in table 5.

PercentGainRule

To define the criteria for determining the wrongly identified rows for *PercentGainRule*, *PercentGain* in respect to *ChargeTime* was evaluated. *PercentGain* is possible to drop down to negative value, for instance when battery consumption goes higher than the charge gain. One scenario to explain such case would be when charging mobile device in a car and at the same time using the device as navigator. Also, remaining battery percent when charging started has an effect on the PercentGain. For example, charging session started with 90% of battery level already available can show only 10 % battery increase in many hours of charging. Considering such scenarios, the criteria for identifying the false positive was defined. Based on the defined criteria, only those cases where *PercentGain* and *CapacityGain* dropped by the same % and the start charge percent was below 90 % were considered to be useful data.

ChargeCapGainRule

As suggested by the error rate check on *PercentGain* and *CapacityGain* shown in Figure 19 and 20 already suggest that error rate at *PercentGain* is only between 0% to 1% which can be minimized to 0% by applying *CycleResultCode* as a check when creating the charging table in the first place. However, the error rate of CapacityGain is between 15% and 17% even after applying the *CycleResultCode* as a check. This suggests that *ChargeCapGainRule* will filter out a significant amount of good data. To suggest the criteria for defining the wrongly identified rows, average percent gain per 10 minutes was calculated and observed from the filtered data by this rule. Based on the criteria set for *ChargeTimeRule,* all the rows containing 7% or more increase over 10 minutes (against the recorded chargetime) were considered good data. Also, only cases where the charge percent was below 90 % were considered.

DischargeTimeRule

The following criteria was set for identifying false positives for *DischargeTimeRule*: *StartDischargePercent > 0 and DischargeTimeBySess > 0 and PercentLoss !=0*. The first check as presented here was that the *StartDischargePercent* had to be greater than zero to make sure that the *DischargeTime* calculated for no battery % left is not included as false positive. The second check (*DischargeTimeBySess*) was to determine that based on *DischargeTime* calculated by taking the difference of *ClientSessionStartDateTime* and *ClientSessionEndDateTime* the *DischargeTime* had to be greater than zero. Finally, *PercentLoss !=0* was to capture the cases where there had been *PercentLoss* against *DischargeTimeBySess*. These criteria could be refined further through an iterative process. However, with these criteria, false positives were already identified. Rows detected by these criteria contained *PercentLoss* that was reasonable against *DischargeTimeBySess.*

DischargePercentLossRule

To identify the false positives for *DischargePercentLossRule*, the following criteria were set: *StartDischargePercent > 0 and CapacityLoss*100/BatCap=PercentLoss and BatCap >0*. For the reason discussed above in *DischargeTimeRule, StartDischargePercent* had to be greater than zero. Next, *CapacityLoss* % was compared with *PercentLoss* to see if both *CapacityLoss* % and *PercentLoss* saw the same changes. Also, check was added to ensure that *BatCap* was greater than zero. *BatCap* had to be greater than zero also to make the second check (*CapacityLoss*100/BatCap=PercentLoss*) valid because *CapacityLoss *100* cannot be divided by zero. With these criteria set, false positives were detected. It was observed that the detected rows contained useful information and therefore were considered to be false positive for *DischargePercentLossRule*.

DischargeCapLossRule

The criteria for identifying false positive for DischargeCapLossRule was determined based on the average battery life observed from the survey portal of the client company. Based on the survey, the average battery life ranges from 22 to 26 hours depending on the model of the mobile device. By taking the average of these two numbers, average battery life was determined to 24 hours which gave hourly 4% loss. Based on this information, the following criteria were defined: *StartDischargePercent > 0 and PercentLoss/(DischargeTime/3600) >4 and DischargeTime > 3600* **.** First *StartDischargePercent* had to be greater than zero for the same reason discussed above for other rules. Next, the main check was made so that *PercentLoss* per hour is greater than 4 and only cases with *DischargeTime* greater than one hour. These criteria can be enhanced through iteration. However, a number of false positives were detected already based on these criteria. Table 5 summarizes the results.

Table 5: False positive rate and confidence interval for data cleaning rules

Rule	No. of Rows Identified	Criteria for identifying false positive	No. of false positive	False Positive Rate	95 percent CI
ChargeTimeRule	229	Hourly % gain against ChargeTime (calculated using ClientSession start and end DateTime) is between 40 -70	3	1.31 %	0.27 % 3.78 %
ChargePercentGain Rule	3287	CycleBatteryStart_Pct is below 90 and PercentGain and Capacity PercentGain are equal	781	23.76%	22.31% 25.25%
ChargeCapGain Rule	79047	CycleBatteryStart_Pct is below 90 and Hourly % gain against ChargeTime is between 40 -70	28751	36.37%	36.04% 36.71%
DischargeTime Rule	6512	StartDischargePercent > 0 and DischargeTimeBySess > 0 and PercentLoss !=0	43	0.66 %	0.48 % 0.89%
DischargePercent LossRule	41675	StartDischargePercent > 0 and BatCap >0 and CapacityLoss*100/BatCap=PercentLoss	28	0.067 %	0.05 % 0.10 %
DischargeCapLoss Rule	48083	StartDischargePercent > 0 and PercentLoss/(DischargeTime/3600) >4 and DischargeTime > 3600	15427	32.10 %	31.66 % 32.5 %

5.3 Minimizing false positive

Data cleaning rules should go through an iteration of rules performance checking to be able to reduce the number of the wrongly identified of rows (false positives). After each iteration, the criteria that was used to identify false positives in the previous iteration should be included in data cleaning rules so that those false positives are addressed by the data cleaning rule. Further, the filtered out data should be examined to see if other false positives can be detected based on some other meaningful criteria. For example, in order to reduce the false positive rate for the rule *ChargeTimeRule* the criteria discussed above should be included within the *ChargeTimeRule*. To sum up, the criteria used to identify false positives can be plugged in with the corresponding data cleaning rules to minimize the false positives. Further, the process of identifying false positives, and minimizing false positive by plugging the false positive criteria in the data cleaning rules. Stepwise this can be as follows: Step (1) apply data cleaning rules, Step (2) collect filtered data by the rules, Step (3) define criteria to identify false positive, Step (4) to minimize false positive rate, include defined criteria of step 3 as part of data cleaning rule, and Step (5) iterate the process of evaluating and minimizing false positive rate to improve data quality.

5.4 Scalability and performance of the ETL

The total time required for an ADF to complete all the tasks depend on the number of pipelines, complexity of data processing queries, and the amount of data. When using on demand clusters, additional time is required for setting up the clusters. Multiple pipelines can run in parallel which can save time. However, most of the time a pipeline cannot be run simultaneously with other pipelines due to dependencies. For example there can be a scenario where pipeline B expects output of pipeline A for its input and in this case Pipeline B cannot be run before pipeline A has finished its job. Figure 21 presents the number of datasets, pipelines, and linked services used in the ADF that was deployed during this thesis work.

There were altogether 16 hive queries used in this ADF for performing data cleaning.

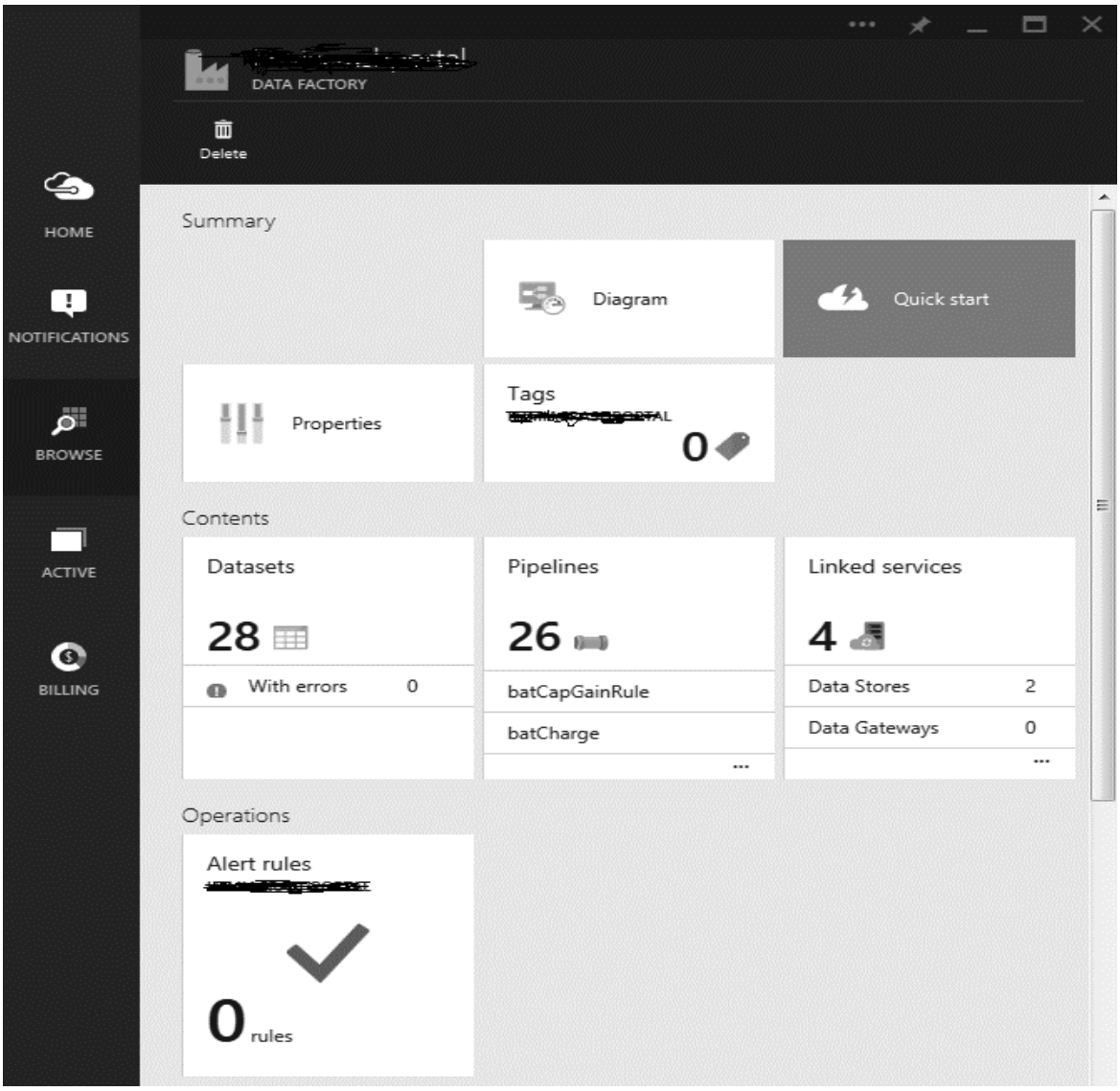
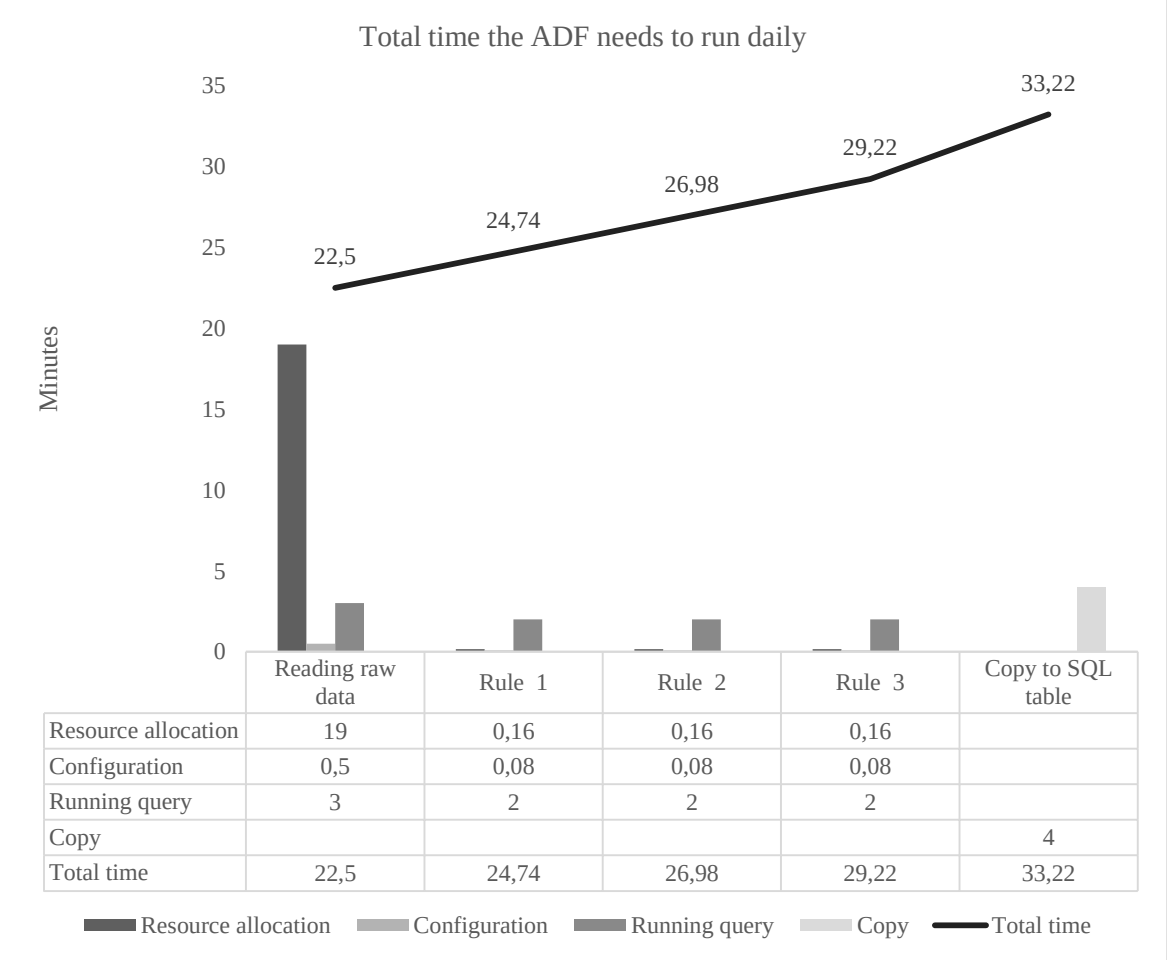


Figure 21: Summary view of the deployed ADF

As shown in Figure 21, the summary view provides a link to diagram view of ADF (presented in Section 3.3, Figure 11) from where all the pipelines can be visualized and monitored. Alert rules can be set to get notified in case of pipelines failure. CARAT and CloudETL do not provide easiness as such for visualizing and monitoring data pipelines. ADF enables ETL developers to be much more efficient by proving easy way of visualizing, monitoring, and maintaining numerous datasets and pipelines from single interface. ADF also proves to be better than CARAT and CloudETL with cost point of view as it allows to use on-demand clusters which in practice means clusters are created only when pipelines need to run compute jobs and those clusters are destroyed as soon as computation is finished and computed data is saved in storage.

The total time required by ADF on a daily basis to finish all the tasks including data processing and data movement was measured against the sample data. These measurements were taken for each of the data cleaning rules. The time required for copying the data cleaned by each rule to SQL table was also measured. The implemented ADF uses on-demand clusters of size four. The time required for setting up on-demand clusters was also observed and measured. Based on these measurements, the total estimated time that ADF should run on daily basis was calculated. Figure 22 presents total estimated time required for the ADF to perform data cleaning and data movement tasks.



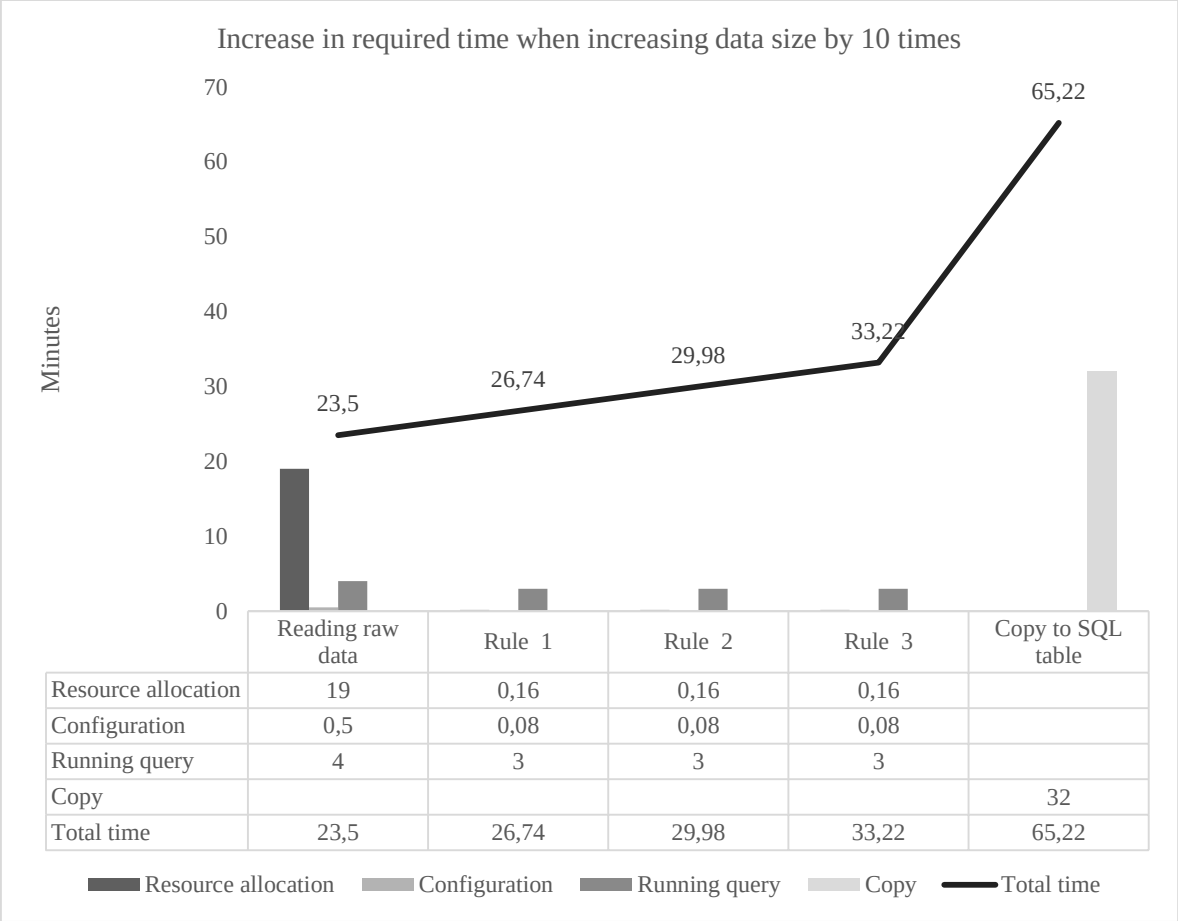
	Reading raw data	Rule 1	Rule 2	Rule 3	Copy to SQL table
Resource allocation	19	0,16	0,16	0,16	
Configuration	0,5	0,08	0,08	0,08	
Running query	3	2	2	2	
Copy					4
Total time	22,5	24,74	26,98	29,22	33,22

Figure 22: Estimated time required for the ADF for processing 286 MB data

As presented in Figure 22, the total time the ADF requires to read raw data, apply three data cleaning rules, and copy the clean data to SQL table is about 34 minutes. On-demand clusters

are set up in the beginning when the first pipeline requiring the on-demand clusters is executed. After the clusters are set up, remaining pipelines can use the running clusters to execute the hive queries. After finishing all the tasks, the on-demand clusters are destroyed. Setting up on-demand cluster can be broken down to two main steps: 1) Resource allocation, and 2) configuration. First resource allocation takes place which takes about 19 minutes. This seems to have a significant impact on overall run time of the ADF which is about 34 minutes. However, this is beneficial as it can save a huge cost if there is no need of running the clusters 24 hours and 7 days a week. On-demand clusters are cost effective because it destroys the clusters after all the jobs are finished which means it stops the price meter as soon as it finishes all the jobs. HDInsight has utility billing model (pay as you go). Configuration takes only about half a minute. The Hive queries took about 3-4 minutes. The first query took about 4 minutes and the rest about 3 minutes. Copying the clean data to an SQL table took about 4 minutes. Pipelines for charging data and discharging data were scheduled to run in parallel as they were independent.

To observe the impact of volume of data over the total required time needed for ADF to finish all the tasks, a 10 times bigger data set was processed. Figure 23 shows total estimated time required for the ADF to perform data cleaning and data movement tasks for 10 times bigger datasets.



	Reading raw data	Rule 1	Rule 2	Rule 3	Copy to SQL table
Resource allocation	19	0,16	0,16	0,16	
Configuration	0,5	0,08	0,08	0,08	
Running query	4	3	3	3	
Copy					32
Total time	23,5	26,74	29,98	33,22	65,22

Figure 23: Estimated time required for the ADF for processing 286 * 10 MB data

Figure 23 indicates that there was minor impact on the data processing when the volume of the data was increased by 10 times. All the hive queries took about a minute more. However, there was dramatic change in the time needed to copy data to SQL. Copying data to SQL table took about 8 times more time than the original sample dataset. This indicates that there should be additional research about how copying data to SQL can be made more efficient. One workaround would be to use a higher powered version of Azure DB. E.g., premium edition. However, due to the limited time of this thesis work and with the fact that the implemented ADF was able to handle the amount of the data of the client company in less than an hour which was considered useful already, the further research on making it efficient to copy data to SQL was scoped out.

5.5 Pricing

MSDN subscription for Visual Studio Ultimate was provided by the client company to test and deploy the ADF. The MSDN subscription gives equivalent of €115 monthly credits of Azure with some additional benefits such as lower rates and no additional charge for using MSDN software on Azure for development and test (Azure Benefit for Visual Studio Ultimate with MSDN 2015). This subscription allows developers to decide about how to use the credits. The developer can choose from an array of available services on Azure platform to use the credits for. To name a few, these services includes Virtual Machines, Websites, Cloud Services, Mobile Services, Storage, SQL Database, Content Delivery Network, Data Factory, HDInsight, Machine Learning, and Media Services.

A number of pricing break downs can be made to learn about the cost of ADF. Table 6 gives an overview of what kinds of costs the implemented ADF involves, and estimated price breakdowns. Comparing the exact price of the ADF against some other cloud service provider such as Amazon Web Service, or suggesting the exact price to process certain amount of data are not within the scope of this thesis. However, an overview of main price factors and their current estimated charge are presented in Table 6.

Table 6: An overview of pricing of ADF (Pricing 2015)

Price factors	Price	Remarks
Blob Storage	Starting cost €3.73 per 100 GB	Geo redundant (6 copies out of which 3 reside in one data center and other 3 reside at least 400 miles away)
Pipelines	6 – 100 activities/month cost €0.2235 per activity	Low frequency (A low-frequency activity occurs once a day or less)
HDInsight Cluster	€0.477/hr for 2 head nodes €0.954/hr for 4 data nodes	A3 (4 cores, 7 GB RAM, 285 GB Disk Size)
ML Studio	€0.14 for per 1000 predictions With 0.1 second per prediction = €0.02	ML API Service (Predictions and Prediction Hours meters are applied concurrently. Prediction Hours are calculated by multiplying the number of predictions by the time per prediction)
SQL Database	11.18 € per month per DB	S0 Standard (DB size = 250 GB, Point in time Restore = 14 days, Database Throughput Units (DTUs) = 10, DTUs are based on a blended measure of CPU, memory, reads, and writes. i.e a performance level with 5 DTUs has five times more power than a performance level with 1)

The above mentioned pricing are based on the implemented ADF. However, as indicated by the above table, the overall pricing for ADF can depend on various factors. These factors can be volume of the data stored in Azure Storage, frequency of the pipelines (how often the pipelines run), SQL database throughput units, number of predictions and predictions to be made in desired fraction of second, number of data nodes in HDInsight clusters. Despite the fact that these costs can be broken down and analyzed either by checking the price on individual service page on Azure or by using the price calculator available on Azure website, a MSDN subscription can fit the business needs and serve most of the purposes.

Chapter 6

Discussions

6.1 Complexity of development and usage

The data quality management system built around ADF and other services such as HDInsight, and ML Studio can claim to hold characteristics such as speed, scalability, maintainability, and cost effectiveness. The proposed architecture for building a data quality management system can be important for both the client company and any other company that wants to make data driven business decisions. Hadoop clusters provided by HDInsight can process a massive amount of data in reasonable time frame. In addition, on-demand clusters can be used to save costs. However, the complexity of building and deploying the system can affect the usefulness. Several updates were found to have been made by azure team already during this thesis work which indicates the development and deployment is constantly getting easier. However, the current limitation of ADF preview portal which forces developers to use Azure PowerShell for deploying datasets, pipelines, and linked services can be cumbersome for those who are not comfortable with Command line interfaces. Also, ADF is still only available in certain zones.

6.2 Use cases

The implemented ADF based data quality management system can serve various use cases. To name a few: **Usecase 1)** There is telemetry data being gathered in Azure blob in text format which needs to be transferred to desired SQL table once, daily or weekly basis, **Usecase 2)** Suppose data stored in text format in Azure blob needs to go through a machine learning model that has been developed in Azure ML Studio to gain predictions or simply need to be processed by running R script on ML Studio. These predictions or the results of R scripts now need to be stored back in Azure blob or desired Azure SQL table, **Usecase 3)**

Suppose there is massive amount of data “Big-data” stored in Azure blob that needs to be analyzed using Hadoop clusters and Hive/pig on HDinsight and store the results back in Azure blob or desired Azure SQL table. Considering these use-cases, and the observed scalability and performance of the ETL built during this thesis represents the right architecture for the data quality management in cloud platforms like Azure. ML studio, and HDInsight seem to be the right combination for applying statistical analysis including machine learning algorithms to Big Data and parallel processing. As an example, with the help of ML studio and HDInsight, it was easy to define data cleaning rules, calculate false positive rates for each data cleaning rules, and also quantify confidence intervals for those false positive rates. Thus, the research questions were answered.

6.3 Learning outcomes

The most significant learning outcomes of this thesis were the skills developed for building and deploying an ETL system for data quality management which can improve the quality of massive amounts of data. This thesis work provided an opportunity to learn and use several data tools and services made available by Azure platform including ADF, HDInsight, Azure Storage, and Azure ML Studio. For the client company, the most significant outcome was the ADF based data quality management system built during this thesis work for improving the quality of the telemetry data and improving data driven business decisions. Testing sample telemetry data was rewarding as it gave chance to learn the process of identifying the data quality problems, forming data cleaning rules, analyzing the false positive rate of the data cleaning rules, quantifying the 95 percent confidence interval for the false positive of a data cleaning rule using R programming, and minimizing the false positive rate of data cleaning rules.

There were also several challenges faced while building and deploying the ADF. One of the learning from those challenges was that it was important to plan the SQL table well enough and in advance. This was important especially due to sequential application of the data cleaning rules. As an example, there were three data cleaning rules applied for charging data. While copying the clean data (data that has passed through all three data cleaning rules) it

was required the number of fields of source (Azure Blob) and destination (SQL table) of the data should match. If for some reason there was mismatch, the copy activity would raise an error and fail. Therefore, it was important to plan well which fields of the raw data should be picked as adding/removing a data field in SQL table would require the similar changes in all data cleaning rules. However, as long as there are no changes in the data fields, sequential data cleaning rules are much easier to add or remove due to their modularity.

6.4 Strengths and weaknesses of the ADF

The key strengths of this ADF based data quality management system are: it is scalable and is capable of handling Big Data, it is modular and easy to maintain meaning that adding or removing data cleaning rules, or scheduling pipelines are simple. In addition, "pay as you go" makes it cost effective. HDInsight facilitates scalable computation with Hadoop clusters and supports for Hive and Pig. ML Studio provides with several useful machine learning algorithms, and also support for R scripting against massive volume of data. ADF provides capabilities to schedule, execute, and monitor data movements and computations. As an example, it is easy to notice from ADF if the pipelines are running properly or if there have been errors. It would not be wrong to say that the ADF based data quality management system is quite robust. However, it also has some limitations. One of the key of limitations is that the current ADF still does not support easy integration with other several services available on Azure platform. For example, the ADF currently does not support integration with MYSQL database. Also, there is no graphical user interface for developing, editing and deploying tables (datasets), linked services (currently only possible for a few services like Azure storage, SQL), and pipelines.

Chapter 7

Conclusions

This thesis aimed to propose a cloud based architecture for building an ETL system for data quality management. In addition, the thesis also aimed to highlight key techniques and technologies currently used in data cleaning. As an outcome of the thesis, the purpose was to build and test a cloud based ETL system for the client company based on the proposed architecture. Consequently, a cloud based ELT system for data quality management, based on the proposed architecture, was successfully built and deployed.

The capabilities of the data quality management system built and deployed during this thesis work was found to be valuable for the client company. As a result, the client company considered to take the system into use for managing the quality of its telemetry data. Also, data cleaning rules applied on the sample data provided by the client company proved to be advantageous. These data cleaning rules performed well in detecting and removing dirty data in order to improve the overall data quality. With the developed ETL system and data cleaning rules, it is clear that a robust cloud based ETL can be built using ADF, which can serve as a data quality management system for a massive amount data. Such system is both highly scalable, and easy to maintain and monitor.

ADF seems to have taken a very general approach to supporting an array of alternative technologies for performing similar tasks, such as use of query language, data storage, machine learning algorithms and (SQL) servers. For example, ADF users are not confined to use Hive query language, rather ADF supports alternatives such as Pig. These kinds of alternatives are in both Hadoop setup and other areas such as data storage. E.g., raw data can be in different forms and format and can be stored either in Azure Blob, Table, Queue, or as File storage. Azure ML Studio and Mahout are two different approaches available for machine learning areas. Similarly, there are MS SQL and SQL servers for dealing with data

available in cloud and on premises. HDInsight already allows to install and use Spark on HDInsight clusters which could be another feature to be supported by ADF. The Azure Data Factory leverages the current approach of MapReduce in Hadoop cluster setup and allows to take advantage of several powerful machine learning algorithms available in Azure ML Studio. The feature of supporting R script via Azure ML Studio, enables data scientists, architects, and statisticians to transform the data based on their needs.

Despite the fact that ADF can be integrated with several other services of Azure, including HDInsight, ML Studio, and Azure SQL, it still lacks integration with several other significant tools on the Azure platform. This lack of integration limits the utility of ADF. For example, the current ADF does not allow copying of data to a MYSQL database. This can limit several developers who like to use MYSQL or other databases like Postgre to benefit from ADF.

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